Residential Flood Risk in the United States:
Quantifying Flood Losses, Mortgage Risk and Sea Level Rise

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Milliman

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Introduction

This Society of Actuaries (SOA) report authored by Milliman, Inc. (Milliman) is designed to evaluate the impact and evolution of societal risk management due to projected future changes in frequency, severity, and variety of weather-related catastrophes.

One catastrophic peril that could be particularly impacted by these changes is flooding. As sea levels rise, so will the risk of hurricane-related inundation to coastal properties, driven by storm surge. Additionally, changes to precipitation patterns could lead to increased risk of inland riverine flooding and urban flash floods.

Under current climactic conditions, flooding stands out among other natural catastrophes in terms of the ongoing risk that it poses to the financial health of the average United States household. Despite recent efforts to reform the National Flood Insurance Program (NFIP), most U.S. homeowners do not carry insurance to protect their properties against the risk of flooding. For most homeowners, the purchase of this coverage is mandatory only if they live in certain specified high-risk areas. However, significant risk exists in areas where the purchase of flood insurance is rare. Additionally, even in areas where flood coverage is required, data from the NFIP and private flood insurers do not indicate high degrees of coverage.

Beyond direct damages to property and communities, the flood insurance protection gap could have many downstream financial impacts. Because homeowners insurance is integral to protecting the collateral that underpins the U.S. mortgage system, coverage gaps could create adverse financial exposure to bearers of mortgage risk including mortgagees, insurers, reinsurers, federal underwriting agencies, and bondholders.

If the frequency or intensity of flooding were to increase, exposed American households could be at more risk in the future than they are today. Further, some areas historically considered to have low flood risk could become more exposed, extending the problem's potential economic impact on the U.S. residential housing stock.

This report examines current countrywide residential exposure to flooding, considers how it could be impacted by sea level rise, evaluates how this could affect the financial health of residential householders, explores a new technique to determine whether it could impair their ability to meet their mortgage obligations, and analyzes the effects of defaults to other parties or institutions.

Executive Summary

This report provides estimates of the insured and uninsured flood exposure of single-family residences in the contiguous United States from both storm surge and inland flooding. Additionally, storm surge losses have been produced across sea level rise scenarios that represent how moderate to extreme interpretations of contemporary scientific projections could affect today's housing stock.

Results are presented below and in the pages that follow, mostly at the Metropolitan Statistical Area (MSA) level. While management of flood risk occurs from the federal jurisdiction down to the individual homeowner, MSA-level results provide an opportunity to identify which local regions may face the most imminent challenges with respect to developing risk-management strategies to address flooding risk. Note the following key findings with respect to our analysis of countrywide single-family flood risk:

- **Building losses to single-family residences due to flood are expected to cost more than $7 billion annually, and more than 87% of those losses are estimated to be uninsured by the NFIP.** If private flood insurance data were included with NFIP data in the estimation of the uninsured loss percentage, it is likely that this estimate would only marginally decrease due to the small size of the residential private flood market relative to the NFIP.

- Building losses to single-family residences due to flood are estimated to average about $78 per single-family residence per year. Other costs to homeowners such as damage to contents and other structures, as well as additional living expenses, mean that **expected total losses for homeowners due to flood are comparable to other major perils typically insured by a homeowners policy, such as fire and wind/hail.**

- Uninsured losses are prevalent across the entire United States. **We estimate that 69% of MSAs in the United States have 90% or more of their expected flood losses uninsured, with only 6% of MSAs having more than 30% of their expected flood losses insured.**

- **Countrywide, we estimate that approximately one-third of homes in the SFHA have an NFIP policy, with the majority of states having less than a 25% take-up rate.** Outside the SFHA, every state except Louisiana, Florida, and Texas has take-up rates of approximately three percent or less, with the majority being less than one percent.

- The increase in storm surge losses due to sea level rise is significant in all storm surge exposed areas, and highly sensitive to the amount of sea level rise. **We estimate that sea level rise will increase total storm surge losses 21% by 2050 in our medium sea level rise scenario, and 66% in our high sea level rise scenario.** Local impacts can be much higher than these averages.

- The severity of extreme flooding events is significantly higher with sea level rise. **Half of MSAs exposed to storm surge currently are expected to have losses from extreme "one-in-500-year" flood events increase by 10% or more in our medium sea level rise scenario. In our high sea level rise scenario, the increase is 17%.**

- MSAs where flooding is already significant relative to income stand to see some of the largest increases in expected flood losses. **The 10 MSAs with the highest ratio of expected flood losses to annual household income today are estimated to have flood losses increase by 0.27% of income in our medium sea level rise scenario and 0.75% in the high sea level rise scenario.**

- **The high percentage of losses uninsured is not expected to improve in the future unless current flood insurance purchase patterns change. The vast majority of additional losses due to sea level rise will continue to be mostly uninsured.** Sea level rise will cause the amount of uninsured losses to increase on an order similar to total losses.

With uninsured losses already relatively high, homeowners will be faced with either increasing uninsured losses or paying for flood insurance policies that they do not have today.

An area of growing concern has been the impact of flooding and sea level rise on the ability of homeowners who financed their residences to pay their mortgages. This report builds on the flood catastrophe modeling results by using them in conjunction with a financial model predicting homeowner default to estimate the degree of mortgage impairment that could potentially result from catastrophic flood events. This was estimated using a sample of loans backing recent credit risk transfer (CRT) securities from the Federal Home Loan Mortgage Corporation (Freddie Mac). We note the following key observations with respect to our modeled estimates of flood impacts to mortgage risk:

- While current insurance purchasing patterns and the mandatory purchase requirement do mitigate the expected impact to credit losses, **model estimates indicate that that at least 42% of the expected increase in credit losses due to extreme flood events could remain after considering the benefits of insurance claim payments.**

- Local impacts of some extreme flood events on mortgage defaults could be substantial, with modeled credit losses an order of magnitude higher post-event. **Even considering current insurance purchasing patterns and requirements, estimated credit losses for impacted regions increased between approximately four and 23 times for each of our modeled events.**

- **Despite the large local impacts, diversification can mitigate most of the credit losses arising from a single extreme flood event on large portfolios of loans similar to those backing Freddie Mac CRT securities**. **We estimate that increased credit losses due to a given extreme flood event ranges between one and five basis points per event across each scenario for an entire collateral pool, after accounting for flood insurance claim payments.** This cost will vary based on the severity of the event and concentration of loans in the pool for a given event.

- **The incremental credit loss impact estimates, while small on the aggregate pool, could deliver a more significant impact to investors in subordinate tranches of CRT mortgage securities. For a subordinate tranche of high loan-to-value loans, we estimated flood events could increase principal writedowns by 15% to 95% relative to a baseline scenario without a flood event**. Thus, the relationship between catastrophic and economic concentrations of risk may be important to consider when evaluating and pricing these transactions.

- Sea level rise can potentially impact credit losses similar to the overall increase in expected losses discussed above. **Increased credit losses due to extreme flood events increased by 24% and 72% using our medium and high sea level rise scenarios, respectively.**

- Each of the points above is in contrast to historical experience of loan performance. In many cases, such as Hurricane Irma, historical experience has been more favorable than these estimates would indicate. We believe there are several intuitive reasons for this, notably **that federal and state financial assistance programs likely provided a significant buffer against credit losses for prior flood events. Thus, the true credit exposure to these events is likely lower than models would indicate, so long as assistance continues to be paid at a rate similar to the one it historically has been.** However, if disaster assistance programs were to be reduced or eliminated, the financial threat posed by this issue could be larger than historical data indicates.

1. The Flood Insurance Gap

1.1 HOW MORTGAGE REQUIREMENTS AFFECT INSURANCE PURCHASE

For homeowners, there is no legal obligation to obtain property insurance. However, insurance purchase requirements apply to most homeowners as a condition of their mortgages, for which insurance is an essential tool for lending institutions to mitigate risk to the collateral that secures their loans. They do this by requiring borrowers to purchase hazard insurance meeting certain guidelines. These guidelines are typically set by federal agencies because the ultimate guarantors of approximately 60% [1]of outstanding U.S. mortgage debt are the government-sponsored enterprises (GSEs). These guidelines shape the coverages and exclusions provided by most insurance policies and are the primary mechanism society has in place to ensure that homeowners maintain proper insurance. As a result, the uptake of various coverages is heavily dependent upon such requirements, and homeowners may incorrectly assume that the insurance they are required to purchase is enough to protect their property from loss.

For flood insurance, purchase is only mandated on federally-backed mortgages for properties located in Special Flood Hazard Areas (SFHAs), defined by flood maps that use boundaries of "one-in-100-year" floodplains. The requirement is a "yes or no" mandate, and could provide poor alignment between coverage and risk for many reasons, including:

- The location of a property outside the "100-year floodplain" does not indicate that there is no flood risk or that the risk is insignificant. The "100-year flood," or, more accurately, the flood with a 1% annual chance of occurring, does not fully capture the range of risk. Estimates indicate that an inch of water in a home from a "less-than-100-year flood" may still be catastrophic, reaching close to $27,000 for a typical home[2]. The 100-year flood can happen in any year and has a 26% chance of occurring over the life of a 30-year mortgage, even assuming a stable climate[3].
- The 100-year floodplain changes over time due to land use and natural factors, but maps only change when government agencies update them.[4]
- The Flood Insurance Rate Maps (FIRMs) defining the 100-year floodplain mostly do not consider precipitation-driven flash flooding, tsunami, or the interaction between riverine and coastal flooding.

Accordingly, although there are existing mortgage requirements intended to ensure that flood insurance is in place in high-risk areas, uninsured exposure to flood risk may exist for many homeowners and mortgages.

2. Methodology: Estimating the Exposure of U.S. Residences to Flood

2.1 DATA AND ASSUMPTIONS

To assess overall flood risk and the flood insurance gap, we paired a realistic cross-section of the U.S. housing stock with data from the NFIP and a catastrophe simulation model, a tool that insurers use to quantify their financial exposure to natural catastrophes. Using this data, we are able to produce estimates of total, insured, and uninsured flood risk not only at the national level but also at a local level so that this issue can be examined for each region and municipality in the country.

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[1] Urban Institute, Housing Finance Policy Center (March 2020). Housing Finance at a Glance: A Monthly Chartbook. Available at: https://www.urban.org/sites/default/files/publication/101926/housing-finance-at-a-glance-a-monthly-chartbook-march-2020.pdf

[2] Federal Emergency Management Agency. Estimated Flood Loss Potential. Available at: fema.gov/media-library-data/1499290622913-0bcd74f47bf20aa94998a5a920837710/Flood_Loss_Estimations_2017.pdf

[3] The 26% probability is equal to one minus the probability of no 100-year flood in each year ($1 - 0.99^{30}$).

[4] See Federal Emergency Management Agency, Flood Map Revision Processes at https://www.fema.gov/flood-map-revision-processes for details of the flood map revision process.

We focused on expected flooding losses for buildings of single-family residences in the contiguous United States as modeled with the KatRisk SpatialKat Flood Model (KatRisk Model). Unless stated otherwise, this definition applies to all references to expected loss contained in this report.

The KatRisk Model comes from a field of analytical tools known as stochastic catastrophe models, which are used for pricing and managing the risk of natural catastrophe risk in the insurance industry. With most catastrophes, and particularly flood, historical data is limited in its ability to predict future events. When provided with input data in the form of a portfolio of exposure characteristics, these catastrophe models provide estimates of losses from future events using accepted scientific and engineering principles, but with smoothed results derived from the execution of thousands of simulation runs.

Insurers typically use these models in conjunction with their own policy data for the purpose of assessing portfolio risk or negotiating reinsurance treaties. For our analysis, the portfolio in question was the stock of U.S. single-family residences.

To build a dataset that could be exposed to the KatRisk model to provide estimated countrywide flood losses, we developed a “market basket” of single-family residences in the contiguous United States. Market baskets are hypothetical datasets used to represent cross-sections of markets. They rely on the actual locations of properties with risk characteristics relevant to flood risk that are estimated with an intent to be as realistic as possible.

We also used NFIP’s OpenFEMA data to estimate which properties were likely to have purchased flood insurance from the NFIP, both inside and outside the SFHAs where purchase is mandated. The impact of private flood insurance is relatively small compared to the NFIP today and has been excluded from our analysis. For further discussion of this point, see Section 2.7.

The final market basket contained approximately 1% of all single-family residences in the contiguous United States—close to 1 million locations. Though this is a credible amount of data when using a catastrophe model for the purposes of this paper, the statistics presented are sensitive to some inherent uncertainty arising from the sampling of locations, assignment of property characteristics, and estimates relating to whether NFIP insurance is in place.

KatRisk model output for the market basket serves as the core for the analysis that follows in this report. Detailed information about the analysis is presented throughout the remainder of the section.

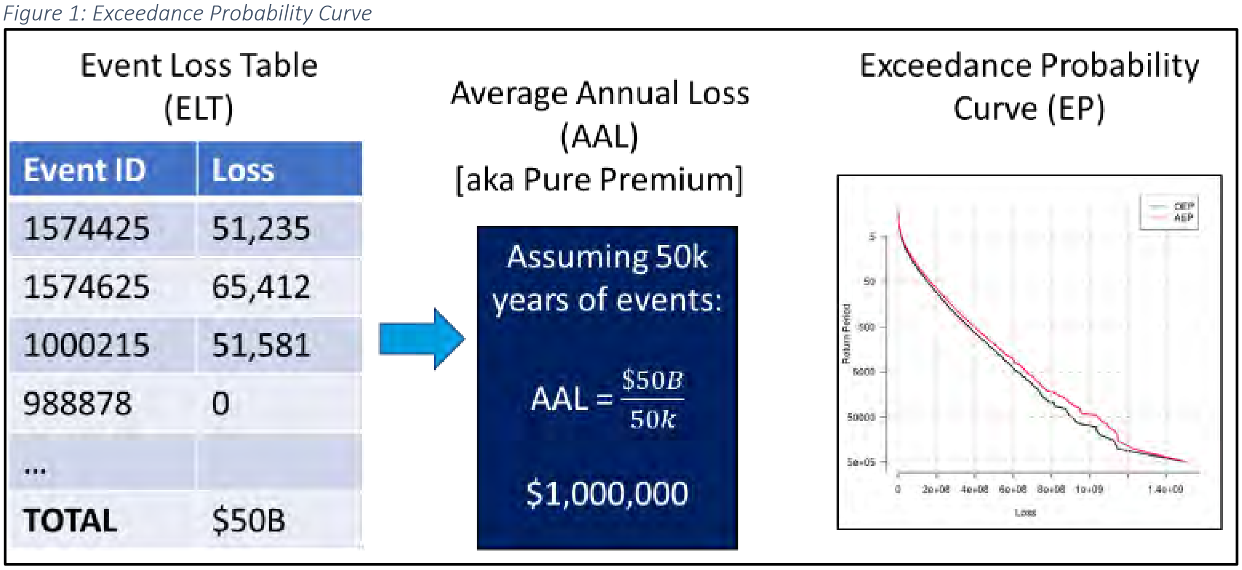
2.2 CATASTROPHE SIMULATION MODELS – A PRIMER

Catastrophe simulation models combine engineering, sciences, and principles of insurance to project future costs associated with natural disasters. In the insurance industry, they have become a fixture upon which the vast majority of catastrophe pricing is based. At their core, these models seek to simulate every realistic potential type of disaster for which a property may be at risk, computing measures of both frequency and severity in the form of return period and average annual loss statistics. The output of these models is then used by actuaries as a synthetic loss history and, along with any actual loss history, can be used to inform an underwriter or homeowner of their potential financial risk over different time horizons. The output from catastrophe models as they pertain to flood risk are especially important in the United States because publicly available insurance loss history for flood is either summarized, sparse, or volatile, making it difficult to know the potential risk of a property.

The primary input to a catastrophe model includes information about each property at risk. The most important of these inputs for computing flood risk include: location, occupancy (e.g., residential or commercial) construction type (e.g., wood, masonry, steel), presence of a basement, elevation of the first floor above ground, number of stories, and the value of different types of property (building, contents, appurtenant structure, interruption of use value). Other important factors may include whether a structure has any enhanced flood defensive measures and any existing insurance limits and deductibles. How a structure is affected by a flood is a function of the materials and composition of the building; detailed building information is required for a catastrophe model to provide accurate results.

After importing the building characteristics into an inland flood and storm surge model, every structure is then exposed to thousands of years of simulated hurricane and rain-storm events. Losses are computed for each of these events both individually and by other aggregates (ZIP code, state, etc.). For each of these aggregation levels, an event loss table (ELT) is computed that tracks the total loss by event. With an ELT, which may be thought of as a simulated loss history, average annual loss (AAL, also known as the pure premium) can be computed. This is determined by summing all the losses and dividing by the number of simulated years. This is referred to as the pure premium because it is the minimum amount an insurance company would need to charge over the entire simulation period to, on average, break even. It is the average loss over every year for a location or aggregation level. Finally, exceedance probability (EP) may be calculated, which relates a probability or return period year with a given loss. As an example: if the one-in-100-year flood loss for a property is $100,000, then every year there is a 1% chance of having a $100,000 or greater loss event at that location. It should be noted that there are two different perspectives of EP curves: occurrence and aggregate exceedance probability (OEP and AEP). OEP simply uses the largest event loss in a given year to compute the EP curve, whereas AEP uses the sum of all events in a given year. The below figure summarizes the three output loss statistics presented above.

Figure 1: Exceedance Probability Curve



2.3 THE KATRISK FLOOD MODEL

The KatRisk flood and storm surge model is based on the simulation of 50,000 years of precipitation and hurricane events, which includes more than 2 million events in the United States and Canada. For the U.S. flood model, primary input data includes precipitation data from the Center for Climate Prediction (CPC) since 1979, forcing data (such as temperature, humidity, and radiation) from the North American Land Data Assimilation (NLDAS) since 1979, stream gauge station data from the United States Geological Survey (USGS), and 10m horizontal resolution elevation data from the National Elevation Dataset (NED).

After obtaining all required data, simulation of inland flood events is performed by first modeling sea surface temperature (SST) globally using a corrected approach.[5] Afterwards, we coupled the principal components of the SST analysis (often referred to as teleconnections, such as El Niño/La Niña, Atlantic Multidecadal oscillation, etc.) to

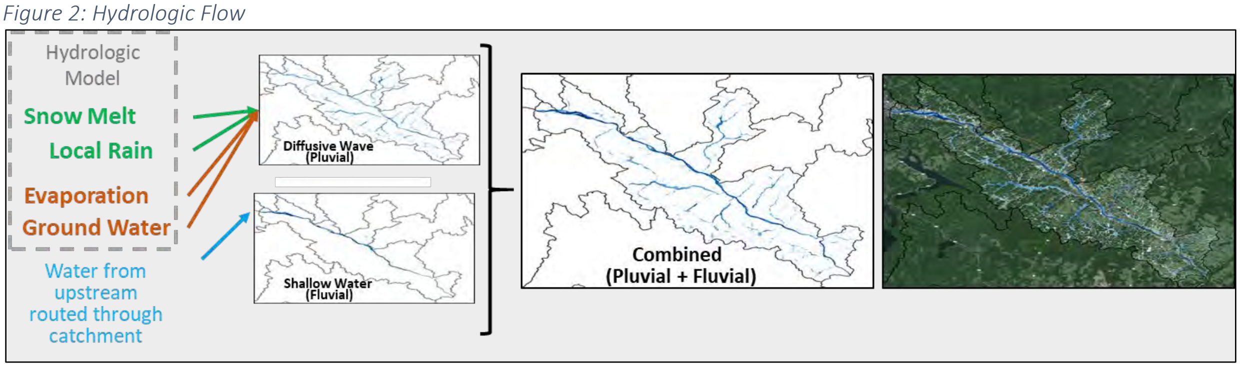
[5] Navarra et al.: A stochastic model for SST for climate simulation experiments, Climate Dynamics (1998) 14: 473-487

precipitation by using a VARMAX state-space model.[6] Next, all major statistical patterns of rainfall and land and sea-surface temperature are computed using the VARMAX model that was built with observed data. Finally, simulation of events of 10 thousand seven-year periods are computed using a combination of historic data and the statistical patterns mentioned above, sometimes referred to as analog models.[7] These data will then cover both events that look similar to history and those events that may be more extreme than history.

Once KatRisk has computed 10 thousand seven-year periods of simulated rainfall, the flow of water downhill toward river outlets must be computed using hydrologic and hydraulic models to capture both the fluvial (river over-topping) and pluvial (surface water) sources of flooding. To compute pluvial flooding, KatRisk first uses a hydrologic model to track all sources and sinks of water over time. This includes but is not limited to snow melt/retention, evapotranspiration, and loss to groundwater. Once the appropriate rainfall/runoff parameters are computed, the model can then determine what percent of the water that falls in a catchment will flow overland and not be lost to the aforementioned sinks. Water is then allowed to fall onto the ground and is routed using a two-dimensional finite volume wave diffusion equation. Computing the fluvial component of flood is accomplished by using the St. Venant equations, which track how water moves from upstream to downstream and out into the ocean. Once the total flow is known along the river, the two-dimensional shallow water equations are used to compute flood inundation. This process is described visually in Figure 2.

In summary, to compute the inland (pluvial and fluvial) components of flood over every simulated year, the general steps as shown below include (1) modeling rainfall and snowmelt, (2) modeling the fraction of rainfall that results in run-off, (3) hydraulic modeling of the water over land surface to streams and rivers, and (4) modeling riverine flow from upstream catchments to downstream catchments. The final step in computing the pluvial/fluvial event set is to discard the first two years of every simulation to ensure that the model has reached a steady state before data is retained.

Figure 2: Hydrologic Flow



The above covers flooding from large (synoptic) scale inland flood events. The KatRisk model also simulates flooding as a result of tropical cyclone-induced extreme precipitation and storm surge. KatRisk has developed a hurricane track set using the HURDAT dataset from 1950 to 2008, which has been filtered to use only pertinent hurricanes. Cyclone genesis is then determined using the rates from the historic record during different seasons and climate cycles, the most important feature being climate patterns related to high and low sea surface temperatures that respectively increase and decrease hurricane generation rates and strength. The movement and intensity of these cyclones is then governed by a combination of physics and statistical likelihood functions over a sea surface with spatial and temporal

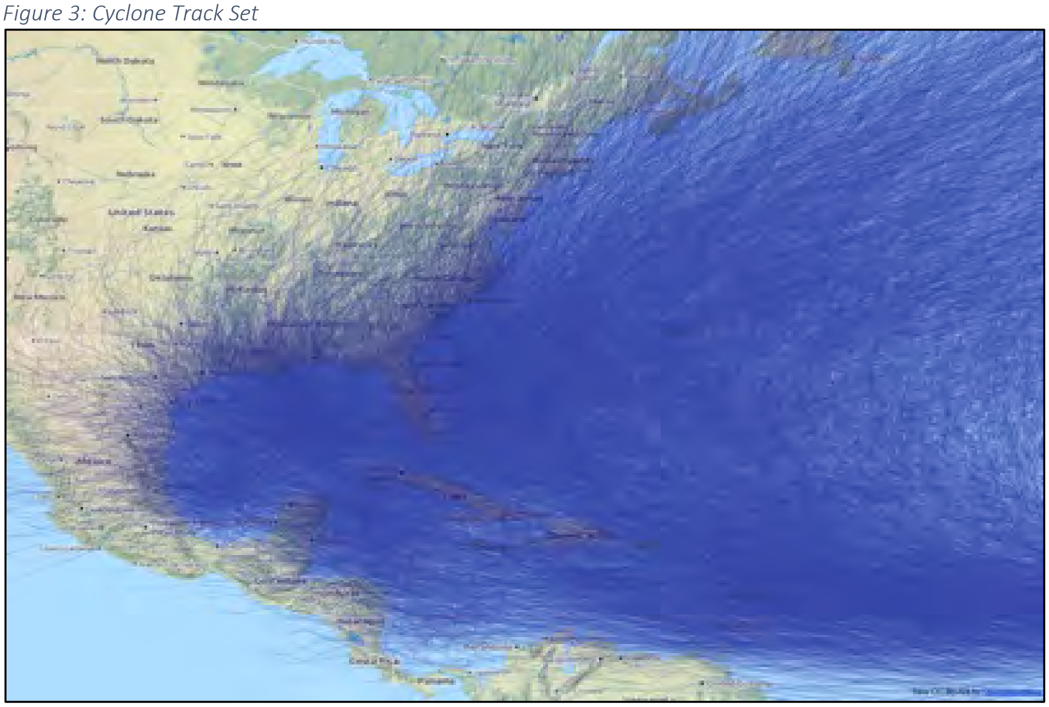
[6] Kedem, B, and Fokianos, K: Regression Models for Time Series Analysis, Wiley, 2002
[7] van den Dool, Huug: Empirical Methods in Short-Term Climate Prediction, Oxford, 2007.

variation. The landfall rate and intensity of these storms is then analyzed to ensure that they generally match historical rates during different seasons and climate states. Finally, tropical cyclone rainfall is computed using physical equations relating statics including but not limited to central pressure and the wind field.

The final track set consists of 50,000 years of tropical cyclone tracks with annual rates and tracks of tropical cyclones dependent on main development region SST and El Nino-Southern Oscillation (ENSO). The main development region is the area between 10^{o} N and 20^{o} N, between the coast of Africa and Central America, where most African waves originate. Each of the 50,000 modeled years is associated with a climate state, making it possible to subset years and events and resulting model losses corresponding to a given climate state, or range of climate states.

Because these events are generated using the same 50,000 years of simulated sea-surface temperatures as the inland flood model, they may be directly combined, creating a model that tracks all primary sources of flood in the U.S., inland and hurricane-induced. Figure 3 provides a sampling of the KatRisk tropical cyclone track set.

Figure 3: Cyclone Track Set



2.4 APPLYING AND SELECTING SEA LEVEL PROJECTIONS

Beyond modeling insured and uninsured risk under current conditions, this report provides estimates of how this risk could change as a result of sea level rise. Our aim was not to project sea levels themselves, but rather to extend our analysis to a future scenario that is plausible and within the range of estimates provided by the contemporary scientific community. It should be noted that we only sought to estimate the potential for increases in storm surge risk due to sea level rise.[8]

[8] Potential changes in other sources of flooding arising from precipitation or river flooding extremes under a non-stationary climate would be significantly harder to estimate. While observations show that "annual precipitation since the beginning of the last century has increased across most of the northern and eastern United States and decreased across much of the southern and western United States," (NCA4) the interplay of precipitation with soil moisture, snow pack, and evapotranspiration is complicated to capture and the uncertainty in estimating the impacts on river floods is an unsolved problem. Following the IPCC special report ("https://www.ipcc.ch/site/assets/uploads/2019/08/4.-SPM_Approved_Microsite_FINAL.pdf) "climate change can

According to the Fourth National Climate Assessment:[9]

> "Global average sea level has risen by about 7–8 inches (about 16–21 cm) since 1900, with almost half this rise occurring since 1993 as oceans have warmed and land-based ice has melted. Relative to the year 2000, sea level is very likely to rise 1 to 4 feet (0.3 to 1.3 m) by the end of the century. Emerging science regarding Antarctic ice sheet stability suggests that, for higher scenarios, a rise exceeding 8 feet (2.4 m) by 2100 is physically possible, although the probability of such an extreme outcome cannot currently be assessed."

These implications led the National Oceanic and Atmospheric Administration (NOAA) to widen its potential outcomes in 2100 from previous studies to be between 0.3m and 2.5m of global sea level rise, and formed the basis

of the analysis of potential sea level rise scenarios in this report.[10] A range of possible outcomes in 2100 for global sea level rise scenarios of 0.3m, 0.5m, 1.0m, 1.5m, 2.0m, and 2.5m broken down by time horizon between 2020 and 2100, with regionally low, medium, and high estimates form the envelope of possible outcomes.

In addition to current sea levels, selections for this analysis were made for "medium" and "high" sea level rise scenarios. The medium regional sea level rise by 2050, with 0.5m globally by 2100, was selected as the medium scenario. The high regional sea level rise by 2050, with 1.5m globally by 2100, was selected as the high scenario.

Once the above selections were determined, the KatRisk storm surge model was modified to reflect the risk under future sea levels. Because the KatRisk Model stores storm surge events as gridded flood depths above datum, it must first subtract the local elevation to determine the local flood height above ground. Sea level rise is then simulated by subtracting local sea level rise from the local elevation. KatRisk then simulates the sea level rise scenarios detailed above by creating two new exposure data sets, each with their local elevations subtracted by the appropriate value to simulate each sea level rise scenario. These conditioned exposure datasets are then run through the KatRisk storm surge and inland flood model. Output is analyzed to obtain AALs and EP curves for all locations and MSA aggregate areas using the methods and models stated above.

2.5 CREATION OF A MARKET BASKET

To assemble the market basket, Milliman obtained parcel data from county assessor records compiled by a third-party data vendor. Each parcel has the latitude, longitude, and other attributes of an actual single-family property.

Beyond the characteristics directly obtained from these parcel records, property characteristics were imputed at each location so that the risk would contain all the necessary input characteristics for catastrophe modeling. To simulate the value of these characteristics, we used a number of public and private data sources to determine the expected distribution of each risk characteristic, where risks with certain characteristics are most likely to be located, and the expected relationships and correlations between characteristic classifications. Data sources include:

- USGS digital elevation maps and FEMA digital flood maps (GIS)

exacerbate land degradation processes (high confidence) including through increases in rainfall intensity, flooding, drought frequency and severity, heat stress, dry spells, wind, sea level rise and wave action, permafrost thaw with outcomes being modulated by land management." However, regional impact, changes in atmospheric patterns as well land management make impact studies very dependent on the underlying assumptions. Many studies that form the basis of the IPCC and NCA4 assessments show that most likely local precipitation extremes will increase. We therefore choose to alter local precipitation intensities and asses those impacts by re-scaling local precipitation extremes with the Clausius-Clapeyron equation that relates the impact on atmospheric water holding capacity with temperature. This gives approximately a 7% increase per 1K temperature increase. Recent studies have found on a global scale similar trends (e.g. Westra et al., Global increasing trends in annual maximum daily precipitation, J.Clim, 2012).

[9] U.S. Global Change Research Program (November 2018). Fourth National Climate Assessment. Available at: https://www.globalchange.gov/nca4

[10] National Oceanic and Atmospheric Administration (January 2017). Global and Regional Sea Level Rise Scenarios for the United States. Available at: https://tidesandcurrents.noaa.gov/publications/techrpt83_Global_and_Regional_SLR_Scenarios_for_the_US_final.pdf

- Industry homeowners quote data obtained from a software company
- Public parcel records, compiled by a data vendor
- Residential Energy Consumption Survey (RECS), published 2009
- Multi-hazard Loss Estimation Methodology (HAZUS), current Flood Model Technical Manual developed by the Federal Emergency Management Agency
- National Association of Insurance Commissioners (NAIC) report: "Dwelling Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance Report: Data for 2015," published 2017

Table 1: Market Basket Attributes and Data Sources

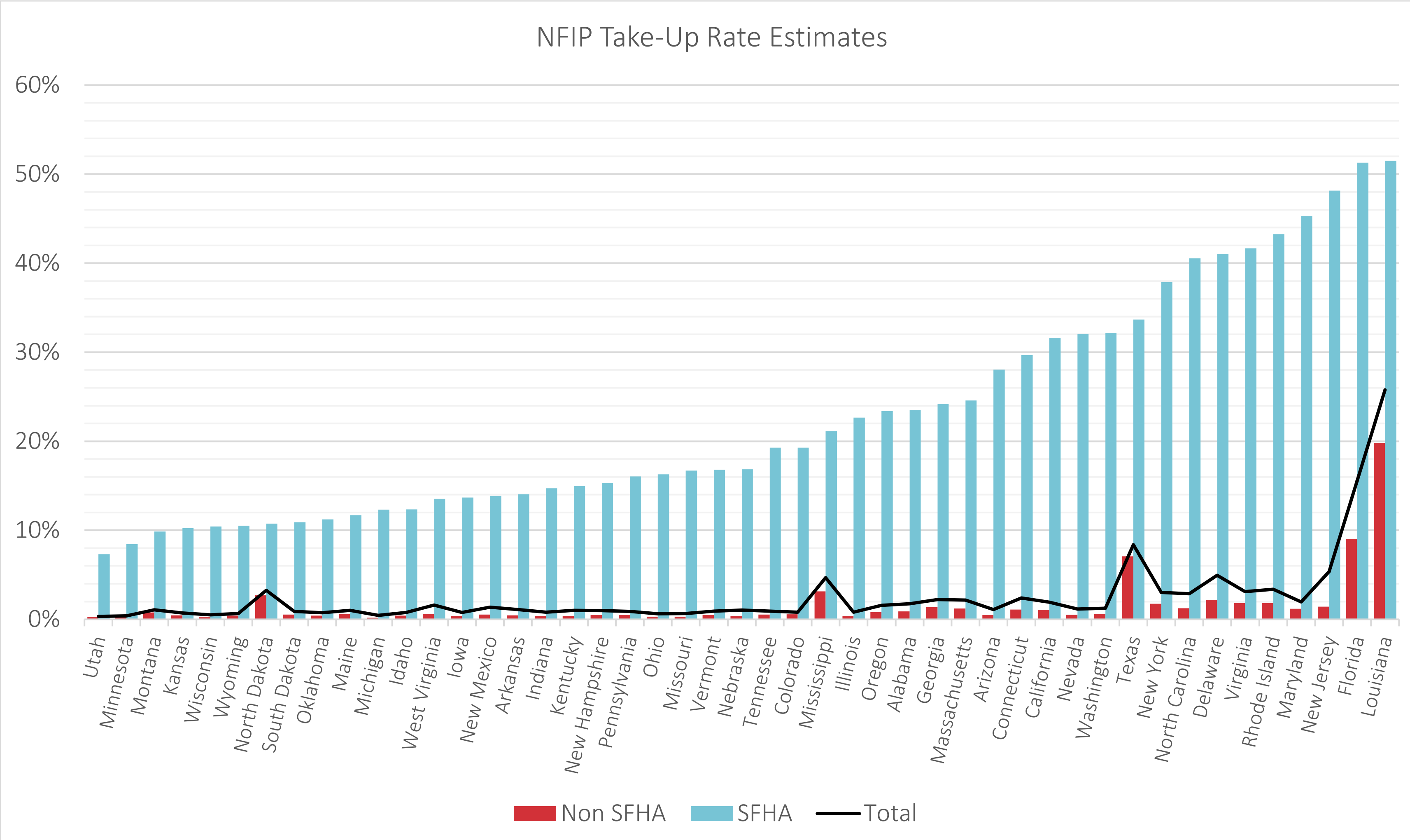
Characteristic	Data Source
Year Built	Parcel Records
Construction	Industry Quote Data
Number of Stories	Industry Quote Data
Foundation Type and First Floor Height	Parcel Records, GIS, RECS, and HAZUS
Building Value and Limit	Parcel Records and NAIC
Site Deductible	Industry Quote Data

2.6 ESTIMATING NFIP TAKE-UP RATE

Once the market basket was developed, we assigned to each risk an assumption as to whether an NFIP policy was present using the following process. First, we used geocoding and FEMA flood maps to determine whether each risk in the market basket was inside or outside an SFHA. We then used the NFIP OpenFEMA data, which provides NFIP policies in force by state, both inside and outside the SFHA, as well as census data, which provides the number of single-family residences in the same areas, to determine the probability than any given home would have NFIP coverage for each combination of SFHA and state. The resulting estimated NFIP take-up rates are shown in Figure 4.

Countrywide, we estimate that approximately one-third of homes in the SFHA have an NFIP policy, with the majority of states having less than a 25% take-up rate in the SFHA. Outside the SFHA, every state except Louisiana, Florida, and Texas has take-up rates of approximately three percent or less, with the majority being less than one percent.

Figure 4: NFIP Take-Up Rate Estimates[11]



[11] For detailed calculations and data sources, see Appendix, Exhibit 7. South Carolina not shown.

We produced the estimates of insured and uninsured losses in the sections that follow by applying the KatRisk model and NFIP take-up rate assumptions to the market basket. At the MSA level, our estimates of insured and uninsured losses are thus dependent on the state(s) in which each MSA is located, and the proportion of single-family residences in and out of the SFHA for that MSA. Thus, the take-up rates used throughout this study reflect the unique risk profile of each MSA based on the location of residences and insurance purchasing patterns in their state(s). However, it should be noted that to the extent that an MSA has unusually high or low take-up rates in the SFHA relative to the remainder of the state, our results for that MSA may be biased.

Our methodology for take-up rate estimation was selected because the intersection of flood maps, parcel data, and OpenFEMA data provides for highly variable results below the state level. Some of these results appear to be driven by data limitations. We found that aggregating to the state level provided more interpretable and stable results. Even when aggregating to the state and SFHA level, estimates of take-up rates in the SFHA for one state, South Carolina, were significantly higher than any other state and did not appear credible. We capped South Carolina take-up rates in the SFHA at the maximum for all other states.

2.7 THE RESIDENTIAL PRIVATE FLOOD INSURANCE MARKET

Recent catastrophes have demonstrated low rates of insurance coverage in affected areas,[12] and uninsured losses are often not fully addressed by post-disaster assistance.[13] Statistics for residential and even single-family homes insured are published by the NFIP, yet public information on the growing private flood market is scarce.

Best estimates indicate that that the majority of reported premiums for private flood are for commercial lines, and that for residential insurance, the ratio of private to NFIP flood writings is small. To benchmark our own estimates of the size of the flood insurance market, and to validate our assumption that private residential flood insurance is relatively immaterial in terms of its impact on the insurance gap today, we examined a number of estimates by independent sources and tabulated them in in Exhibit 1 on the following page. Each estimate shown quantifies some aspect of the residential or private flood insurance market. Because the flood insurance market is growing steadily and changing over time, it may be important to consider the time at which any estimate was made in addition to the estimate itself.

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[12] Milliman (July 2018). Available at: https://milliman-cdn.azureedge.net/-/media/milliman/importedfiles/uploadedfiles/insight/2018/ny-nj-market feasibility.ashx

[13] Congressional Budget Office (April 2019). Expected Costs of Damage From Hurricane Winds and Storm-related Flooding. Available at: https://www.cbo.gov/system/files/2019-04/55019-ExpectedCostsFromWindStorm.pdf

Exhibit 1: Estimates of Private Flood Insurance Written

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Private Flood compared to NFIP Based on Statutory Accounting Data (Note 2)		Estimates of Residential Percent of Flood Market						
	NFIP Earned Premium (Note 1)	Private Flood Earned Premium (Note 2)	Private Flood as % of Private +NFIP (3)/[(2) + (3)]	WSIA (Note 3)		Carrier Management (Note 4)		Wharton Private % of Total Policies	III Survey % of Homeowners with Flood Insurance (Note 6)	NAIC Survey % of Residences with Flood Insurance (Note 7)
Year				Residential	Residential % of Total	Residential	Residential % of Total	Residential Primary (Note 5)		
2013	$3,512,987								14%	
2014	3,542,525								14%	
2015	3,436,750								14%	
2016	3,332,142	$239,456	6.7%	$120,224	32.0%				12%	
2017	3,308,151	599,562	15.3%			$220,000	34.9%	3.5% to 4.5%		
2018	3,327,327	659,467	16.5%	161,432	34.0%	213,000	31.3%		15%	
2019										17%

Notes:

1. https://www.fema.gov/total-earned-premium-calendar-year. Dollar amounts in thousands.
2. (3) from SNL.com database of statutory annual statement for P&C industry. Dollar amounts in thousands.
3. Wholesale and Surplus Lines Insurance Association, Surplus Lines Flood Insurance Market Data and Statistics. January 24, 2017. and February 28, 2019
   https://www.wsia.org/docs/PDF/Legislative/Surplus%20Lines%20Market%20Data%20and%20Statistics%201-24-17%20w%20attachement.pdf
   https://www.wsia.org/docs/PDF/Legislative/SurplusLinesMarketDataandStatistics2-28-19.pdf
4. Carrier Management - Private Flood Insurance Report - 2019. Dollar amounts in thousands.
   https://www.insurancejournal.com/research/app/uploads/2019/06/FINAL-Private-Flood-Insurance-Report-2019.pdf
5. Kousky, et al. "The Emerging Private Residential Flood Insurance Market in the United States" Wharton Risk Managament and Decision Process Center.
   http://www.floods.org/ace-files/documentlibrary/committees/Insurance/Emerging_Flood_Insurance_Market_Report-Wharton-07-13-18.pdf
6. Insurance Information Institute (III) - Insurance Factbook 2019, based on Pulse surveys conducted by III.
   https://www.iii.org/sites/default/files/docs/pdf/insurance_factbook_2019.pdf
7. https://naic.org/Releases/2019_docs/naic_survey_flood_insurance.htm

A 2017 report from Wharton provided a range of 3.5% to 4.5% (column 9) as the percentage of total residential flood insurance policies attributable to the private market. NFIP take-up rates countrywide were approximately 3.5% in 2018 for single-family homes.[14] Accounting for the high end of Wharton's range suggests that no more than 3.7% (1.045 * 3.5%) of single-family homes in the United States have flood insurance of any kind, far below the recent Insurance Information Institute (III) and NAIC survey results of 15% and 17%, shown in columns 10 and 11 above. While the surveys shown are for slightly different sets of the residential market, single-family homes represent most of the housing stock in the United States. We note that these survey estimates appear to reflect consumer sentiments, and it is possible that the results indicate an incorrect belief among some uninsured consumers that flood coverage is in place. The NAIC has commented that it also expects this to be the case.[15]

We compared the 3.7% single-family flood insurance take-up rate derived above to estimates of the surplus lines and admitted residential flood markets shown in columns 5 and 7. Summing these premiums, we estimate that the private residential flood market premium totaled about $374 million in 2018, close to 10% of the total residential flood market premium when including the NFIP. This is about twice as high as the Wharton estimate, but not necessarily in conflict, as the Wharton estimate is based on policy counts and not premium.

Whether looking at policy counts or premium, public data supports the notion that the size of the private residential flood market relative to the NFIP is small as assumed in this report. We find that all data and independent estimates provide corroborative evidence that despite encouraging recent growth, the private residential flood insurance market remains relatively small, with almost all homeowners flood policies currently written by the NFIP. Thus, while our characterization of uninsured flood risk in this report could be overstated because it relies on the assumption that NFIP is the only provider of residential flood insurance, the small size of this market today means that any bias resulting from this estimate should also be small.

[14] NFIP single-family policies in 2018 (which include mobile homes) were 3.54 million in 2018 for the United States (https://bsa.nfipstat.fema.gov/reports/w2rpcnta.htm), compared to 99.97 million single-family and mobile homes in the 2017 five-year American Community Survey, provided by the United States Census Bureau. 3.54 / 99.97 = 3.5%

[15] As quoted in the NAIC press release (https://naic.org/Releases/2019_docs/naic_survey_flood_insurance.htm) by Eric Cioppa, NAIC president and superintendent of the Maine Bureau of Insurance, "This disparity perhaps reflects the common, though incorrect, assumption that homeowners insurance covers flooding."

3. Results: Estimates of Insured and Uninsured Flood Exposure to U.S. Homes

The extreme catastrophic nature of floods can make it problematic to project future losses based on past flood events, particularly in the face of changing hazard presented by sea level rise. We used a catastrophe simulation model to produce estimated flood losses for each location in the market basket, with our resulting dataset providing two key features that cannot be obtained using only historical flood data: 1) An estimate of total losses, including losses for homes not insured and 2) a projection of future expected losses using future sea level rise scenarios.

3.1 INSURED AND UNINSURED LOSS RESULTS

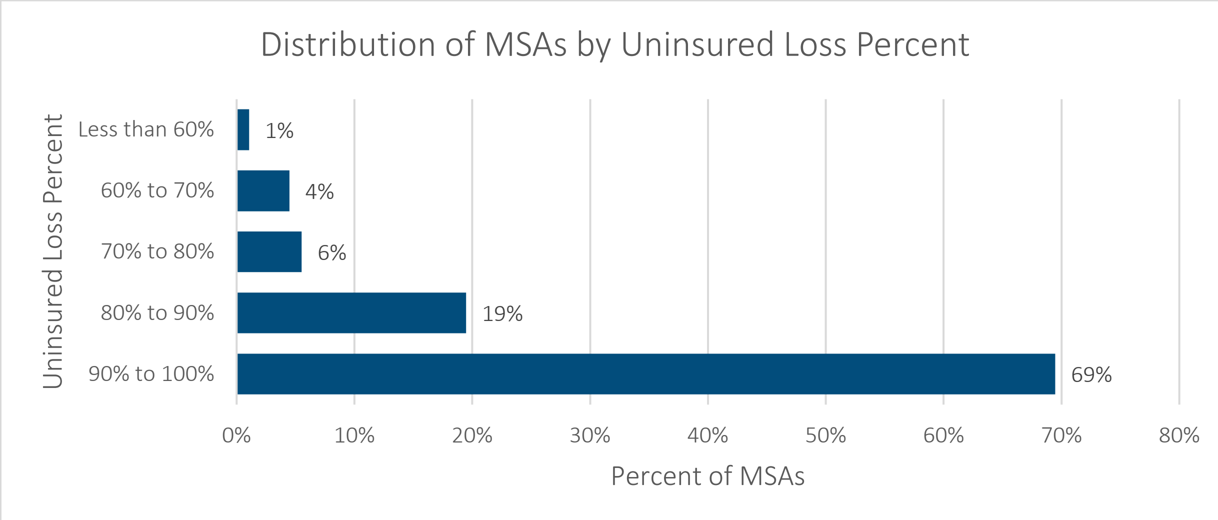
The output of this process is detailed in Exhibit 8 of the Appendix, which shows modeled output of average annual losses, the resulting portions that are expected to be insured versus uninsured, and an ultimate estimate of the percent of losses uninsured for all 380 MSAs in the study area. **We estimate that losses to single-family residences due to flood are expected to cost more than $7 billion annually, with more than 87% those losses being uninsured by the NFIP.** The combination of insured and uninsured flood losses are significant relative to other perils typically covered for single-family residences, such as fire, non-flood water, and wind.[16] Countrywide, the average homeowner has $78 of expected annual flood losses to their building alone. Costs incurred for losses to contents, additional living expenses (ALE), and losses to other structures aside from the primary residence would be in addition to the $78 average.[17]

Individual and community-level flood risk is skewed, with portions of the populations having flood risk that is orders of magnitude higher than others. Even when aggregated at the MSA level, our findings indicate that many areas have high average expected losses and are mostly uninsured. As seen in Figure 5, **an estimated 69% of MSAs in the United States have 90% or more of losses uninsured, with approximately 5% of MSAs having more than 30% of their expected flood losses insured.** The MSAs with the highest portion of insured loss are mostly in Florida and Louisiana, with a handful of others in Atlantic states and Texas. MSAs range from mostly uninsured when total expected flood losses are high, and nearly entirely uninsured in areas that are generally not exposed to storm surge losses from tropical cyclones

[16] Multiplying weighted average claim frequency and severity for homeowners from 2013 to 2017 results in estimated average losses of $191, $214, and $210 for the perils of fire and lightning, wind and hail, and water damage and freezing, respectively. In addition to building losses, these estimates include losses to contents, additional living expenses, and losses to other structure. Source: Insurance Information Institute. Facts + Statistics: Homeowners and renters insurance, Average Homeowners Losses, 2013-2017 (1), referencing ISO®, a Verisk Analytics® business. Available at: https://www.iii.org/fact-statistic/facts-statistics-homeowners-and-renters-insurance

[17] Using OpenFEMA data, we estimate that contents coverage only accounts for 16% of the total building and contents losses paid by the NFIP since 2010, and also only accounts for 15% of the insured limits among policies that had losses. This shows that contents losses are roughly the same, relative to their NFIP insured limits, as building losses. Extrapolating to building value suggests that a homeowner with contents equal to 50% of their building value, for example, would shave expected building and contents flood losses roughly 50% higher than just building flood losses. ALE and other structures-specific flood loss data are not available from this data.

Figure 5: Distribution of MSAs by Uninsured Loss Percent



With regard to the magnitude of both insured and uninsured losses, 27 of the 48 states studied have at least one entire MSA with average expected losses of more than $100 per single-family residence. This statistic does not mean that the other 21 states have low flood risk, as they tend to be lower-population states with a limited number of MSAs, such as Rhode Island, Vermont, and Wyoming, which only have four MSAs designated between them. Further supporting the fact that flood is a countrywide peril, six of the top 20 MSAs by total expected annual flood losses are in the West or Midwest.

3.2 IMPACTS OF SEA LEVEL RISE

Focusing on exposure to storm surge, we sought to understand how uninsured losses would be impacted by changes in sea level rise. Table 2 shows that, under each sea level rise scenario, the percent of losses uninsured is relatively unchanged. The high percentage of losses uninsured is not expected to improve in the future unless current flood insurance purchase patterns change. Sea level rise will cause the amount of uninsured losses to increase on an order similar to total losses. With uninsured losses already relatively high, homeowners will be faced with either increasing uninsured losses or paying for flood insurance policies that they do not have today.

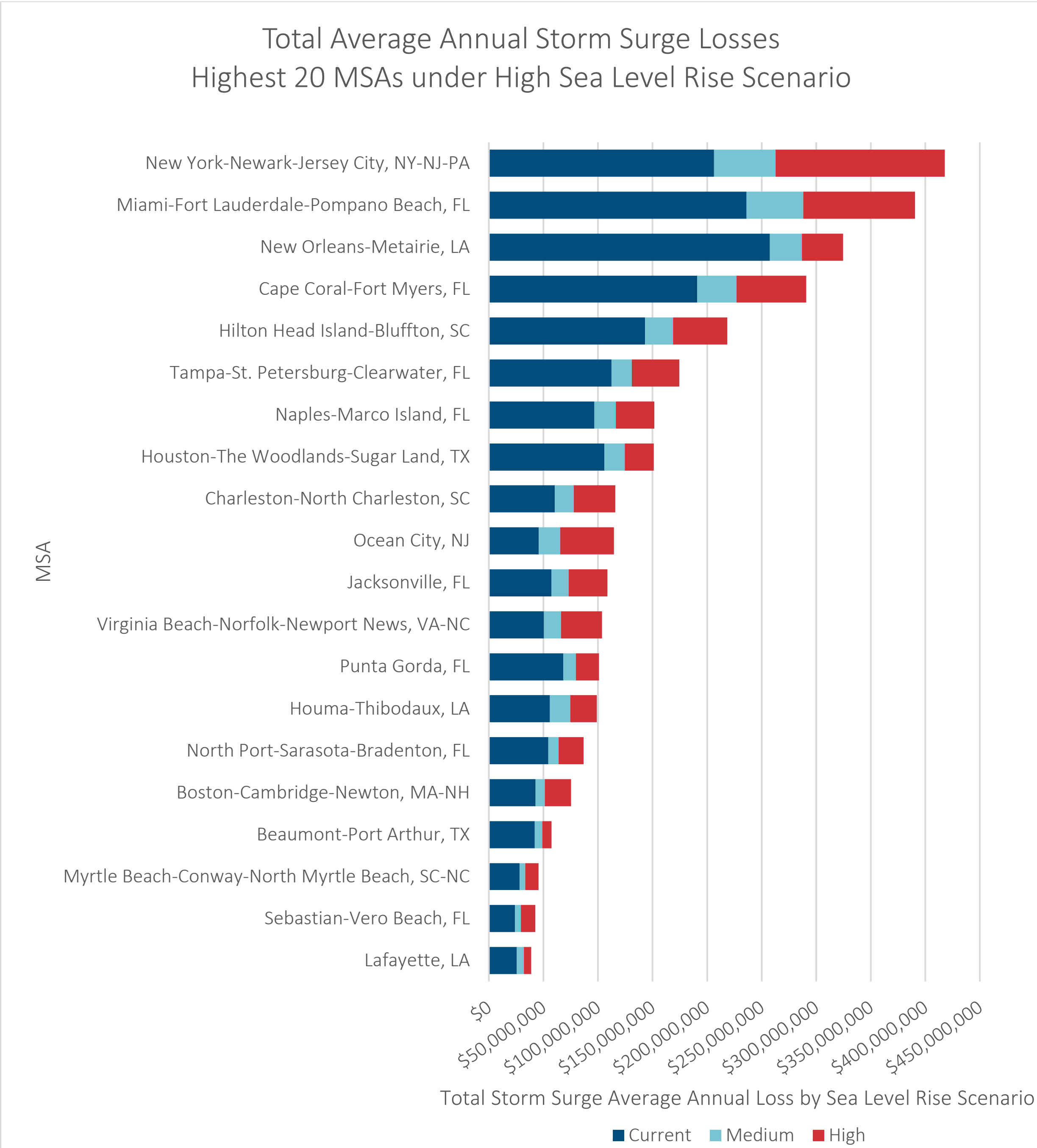
Table 2: Summary of Total Annual Storm Surge Losses by Sea Level Rise Scenario

Annual Storm Surge Losses	Current Sea Levels	Medium Sea Level Rise	High Sea Level Rise
Insured (millions)	$601	$728	$989
Uninsured (millions)	$1,776	$2,155	$2,949
Total (millions)	$2,376	$2,883	$3,938
Uninsured Percent of Total	75%	75%	75%
Change in Total Relative to Current Sea Levels	N/A	21%	66%

In addition to calculations supporting Table 2 above, MSA level results for storm surge losses by sea level rise scenario can be found in Exhibits 9 to 12 of the Appendix. Under our medium sea level rise scenario, total storm surge losses increase an average of 21% and up to a maximum of just over 50% by MSA. In a high sea level rise scenario these numbers increase to 66% on average, and a maximum of over 200%. **These statistics indicate a high sensitivity in future storm surge losses due to sea level rise, as the increase in total storm surge losses between the medium and high scenario averages over 300%.**

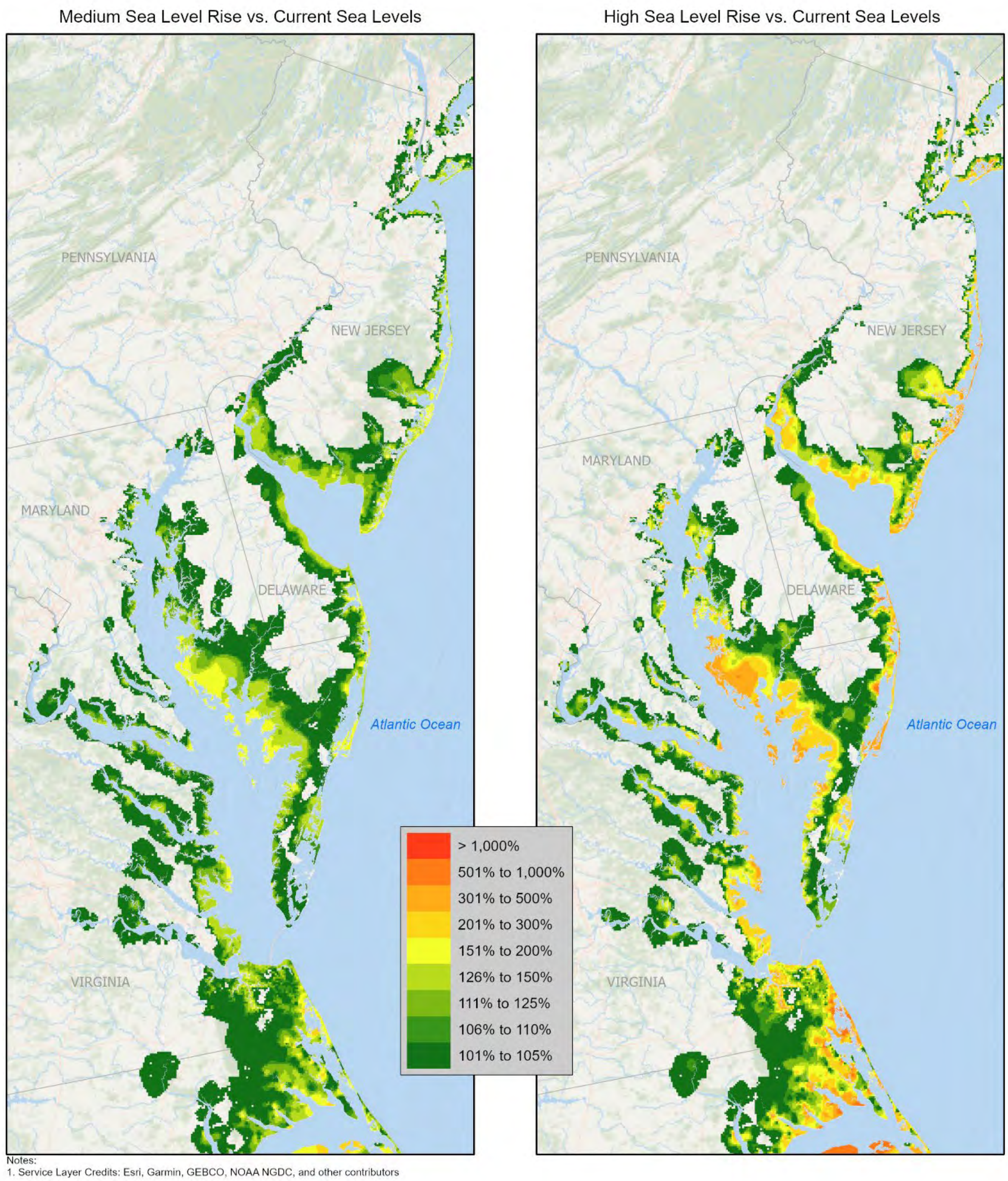
Figure 6 further illustrates how sea level rise impacts will vary regionally. At current sea levels, we estimate that the New Orleans-Metairie MSA has the most expected losses due to storm surge. In a medium sea level rise scenario, Miami-Fort Lauderdale-Pompano Beach would have the highest expected losses, and for the high sea level rise scenario it would be the New York-Newark-Jersey City MSA.

Figure 6: Storm Surge Losses by MSA and Sea Level Rise Scenario



To view sea level rise impacts visually, we developed Figure 7, which maps the increase in losses due to the impacts of sea level rise on total flood losses for several Middle Atlantic states. The increase in losses are spatially smoothed to show how the increase in total flood losses changes with geography, even in areas that may not be represented in the market basket. Maps for other regions of the country and a description of the spatial smoothing process are provided in the Appendix.

Figure 7: Increase in Total Flood Losses: High vs. Medium Sea level Scenarios, Middle Atlantic States



While the Mid-Atlantic states tend to have lower storm surge losses than lower Atlantic and Gulf states, the increase in total flood losses due to sea level rise is estimated to be the highest from North Carolina to New York (above and Maps 3 to 5 in the Appendix).

By appending census estimates of median household income to the market baskets, we estimated the magnitude of the costs of flooding relative to current incomes. Table 3 shows these results for selected MSAs exposed to storm surge. The resulting estimates show the average ratio of location level losses to income, by MSA, under each sea level rise scenario.

AALs for both storm surge and inland flood are important metrics and are increasingly used by insurers to set prices for flood insurance premiums. For insurers that do so, changes in AAL would be expected to be correlated with changes in insurance premiums. Homeowners either would bear the cost of increased prices in insurance premiums or increased flood losses depending on whether or not they purchase insurance.

The ratio of AAL to median income is highly skewed, with a few MSAs having relatively high ratios. Table 3 illustrates this, showing the 20 highest ratios at current sea levels, and the associated expected increases as sea levels rise. Flood is a peril that can present extreme risk in certain areas, which means that every MSA has homeowners that will have high costs of flooding relative to income. However, these results point to which MSAs may be particularly subject to either high insurance premiums, possible flood losses, or both. At current sea levels, only Hilton Head Island-Bluffton, SC is estimated to have AALs average over 2% of median incomes, but In the medium sea level rise scenario, Houma-Thibodaux, LA and Punta Gorda, FL are also estimated to have AALs exceed 2% of median incomes.

Table 3: Ratio of Average Annual Loss to Census Block Group Median Household Income – Averaged by MSA[18]

MSA	Current Sea Levels	Medium Sea Level Rise	High Sea Level Rise
Hilton Head Island-Bluffton, SC	2.13%	2.52%	3.29%
Houma-Thibodaux, LA	1.87%	2.50%	3.32%
Punta Gorda, FL	1.89%	2.21%	2.78%
Naples-Marco Island, FL	1.37%	1.65%	2.16%
Cape Coral-Fort Myers, FL	1.24%	1.48%	1.88%
New Orleans-Metairie, LA	1.25%	1.39%	1.57%
Ocean City, NJ	0.88%	1.26%	2.21%
Beaumont-Port Arthur, TX	0.75%	0.86%	1.00%
Jacksonville, NC	0.73%	0.83%	1.04%
Lake Charles, LA	0.66%	0.80%	0.98%
Homosassa Springs, FL	0.63%	0.71%	0.86%
Sebastian-Vero Beach, FL	0.46%	0.54%	0.74%
Lafayette, LA	0.38%	0.48%	0.58%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	0.37%	0.42%	0.54%
Wilmington, NC	0.36%	0.40%	0.50%
Charleston-North Charleston, SC	0.31%	0.40%	0.59%
North Port-Sarasota-Bradenton, FL	0.34%	0.38%	0.50%

[18] For detailed calculations, data sources, and a complete table for storm surge exposed MSAs, see Appendix, Exhibit 13

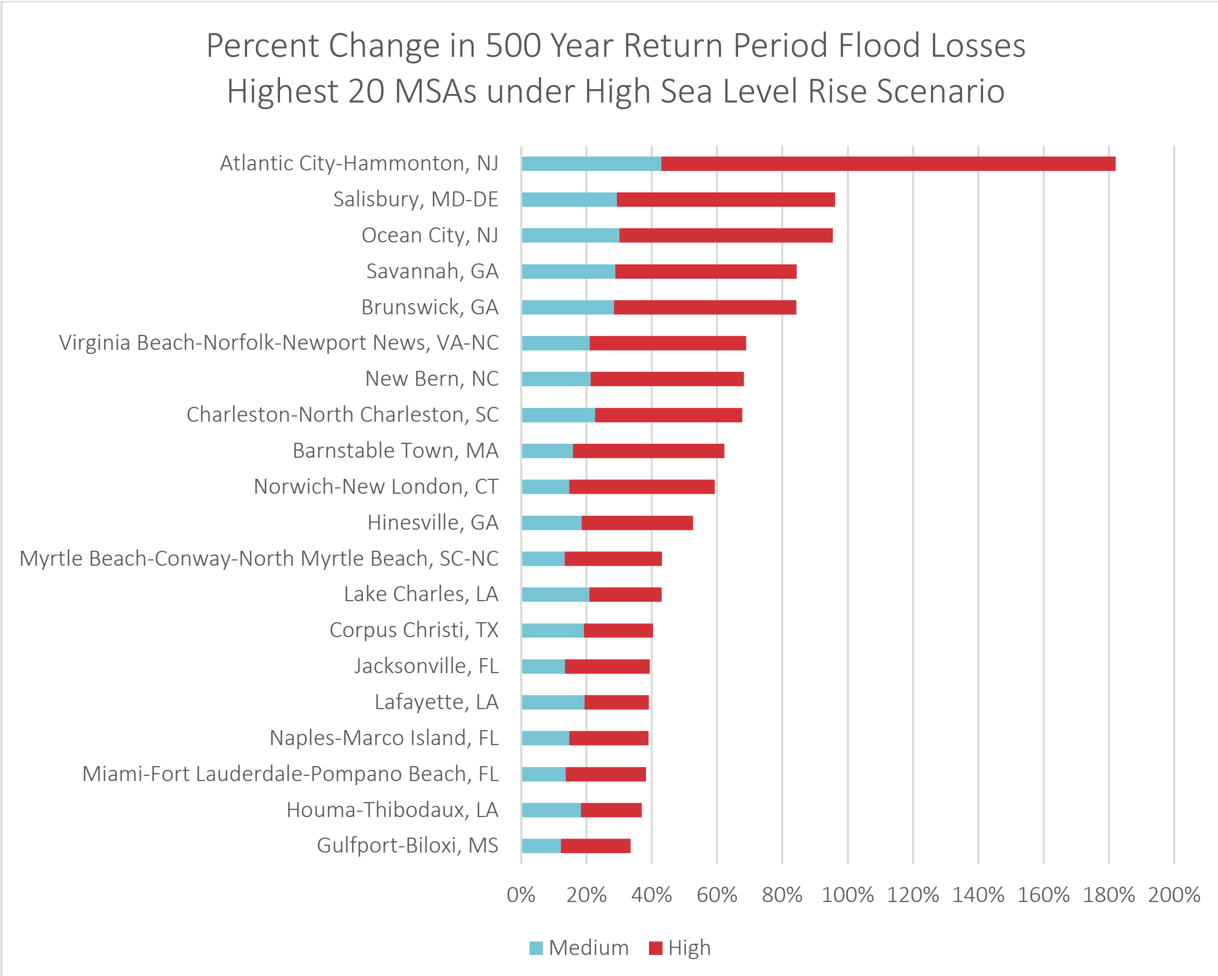
The risk of extreme events has always had a major impact on the private flood insurance market. This risk, and the inability to calculate it, has been part of the reason why private flood insurers have not offered significant amounts of flood coverage in the past. All else equal, affordability and availability of insurance premiums will likely be adversely impacted as the risk of extreme events occur in an area, as insurers and reinsurers will raise rates or refuse to accept risks to preserve profitability and solvency.

Exhibit 14 of the Appendix shows increases in the risk of extreme (one-in-500 year)[19] events under the medium and high scenarios. Similar to AAL changes, changes in the costs of extreme events are highly correlated between the medium and high scenarios but are also highly sensitive to sea level assumptions. **The average increase in 500-year losses with high sea level rise tends to be about three times higher than with medium sea level rise.**

Figure 8 below shows the percent change in these extreme flood events for the MSAs with the highest increase in expected flood losses from extreme events. While Florida and Louisiana have some of the highest risk of storm surge today, the greatest increases in losses for extreme events tend to be along the Atlantic Coast north of Florida. **The eight MSAs with the largest percent increases in either sea level rise scenario are in all between Georgia and New Jersey.** New Jersey MSAs are particularly vulnerable, with two showing the highest percent increases in the medium sea level rise scenario among all MSAs.

[19] One-in-500-year scenarios are based on the OEP curve of event losses. The one-in-500-year loss for a given region is the event loss that has a chance of being exceeded with an annual probability of 0.2% (1/500).

Figure 8: Change in 500-year Return Period Flood Losses for Sea Level Rise Scenarios Compared to Current Sea Levels



3.3 SUMMARY OF RESULTS BY MSA

Compiling the model output and metrics developed, we take a broader look at the different risks faced by MSAs with respect to sea level rise in Exhibit 2. The selected scenario in this case is medium sea level rise.

Exhibit 2: Summary of Flood Losses by MSA – Medium Sea level Rise vs. Current Sea Levels

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Exposure Metrics under Current Sea Level						Exposure Increase Metrics under Medium Sea Level Rise			
Metropolitan Statistical Area Title (Note 1)	Total Annual Losses (Note 2)	Total Annual Losses Rank (Note 3)	Percent of Losses Uninsured (Note 4)	Percent of Losses Uninsured Rank (Note 5)	AAL to Income Ratio (Note 6)	AAL to Income Ratio Rank (Note 7)	Percent Increase in Total Loss (Note 8)	Percent Increase in Total Loss Rank (Note 9)	Percent Increase in 500 Year Return Period Loss (Note 10)	Percent Increase in 500 Year Return Period Loss Rank (Note 11)
Atlantic City-Hammonton, NJ	$4,761,940	54	62.8%	58	0.1%	51	44.1%	1	42.9%	1
Ocean City, NJ	45,806,409	18	72.7%	46	0.9%	7	42.8%	2	30.1%	2
Salisbury, MD-DE	15,973,654	37	60.0%	62	0.1%	43	40.3%	3	29.3%	3
Houma-Thibodaux, LA	55,876,027	15	72.3%	47	1.9%	3	33.6%	4	18.3%	13
Brunswick, GA	7,657,390	47	87.1%	22	0.3%	21	30.8%	5	28.4%	5
Corpus Christi, TX	7,255,456	48	90.2%	10	0.1%	45	29.2%	6	19.2%	11
Charleston-North Charleston, SC	62,080,754	14	67.5%	52	0.3%	17	28.0%	7	22.7%	6
Virginia Beach-Norfolk-Newport News, VA-NC	55,407,985	16	78.2%	37	0.1%	41	28.0%	8	20.9%	8
Savannah, GA	11,081,849	43	86.1%	25	0.1%	39	27.3%	9	28.8%	4
New Bern, NC	4,444,006	55	78.1%	38	0.2%	28	25.7%	10	21.2%	7
Lafayette, LA	26,692,981	25	61.6%	61	0.4%	13	23.6%	11	19.4%	10
Jacksonville, FL	68,047,575	12	80.8%	32	0.2%	26	22.7%	12	13.4%	18
Vineland-Bridgeton, NJ	788,067	61	51.7%	63	0.0%	58	21.8%	13	11.9%	21
Lake Charles, LA	20,273,215	32	67.8%	51	0.7%	10	21.8%	14	20.8%	9
Sebastian-Vero Beach, FL	26,478,775	26	93.0%	5	0.5%	12	20.9%	15	10.7%	30
Naples-Marco Island, FL	96,781,625	8	64.7%	55	1.4%	4	20.2%	16	14.7%	16
Cape Coral-Fort Myers, FL	191,457,026	5	66.5%	54	1.2%	6	18.9%	17	10.9%	27
Hilton Head Island-Bluffton, SC	143,457,248	6	88.7%	16	2.1%	1	17.8%	18	10.8%	29
Hinesville, GA	721,087	63	98.6%	2	0.1%	54	17.7%	19	18.5%	12
Miami-Fort Lauderdale-Pompano Beach, FL	296,245,156	2	77.4%	41	0.3%	20	17.2%	20	13.6%	17
Punta Gorda, FL	68,115,329	11	63.7%	57	1.9%	2	17.1%	21	8.6%	37
Barnstable Town, MA	14,117,678	39	94.0%	3	0.2%	30	16.7%	22	15.9%	14
Beaumont-Port Arthur, TX	42,592,102	19	90.9%	8	0.7%	8	16.2%	23	11.0%	25
Deltona-Daytona Beach-Ormond Beach, FL	29,902,256	22	77.4%	40	0.2%	24	15.8%	24	11.1%	24
North Port-Sarasota-Bradenton, FL	63,139,612	13	68.1%	50	0.3%	16	14.8%	25	10.9%	26
Gulfport-Biloxi, MS	16,960,076	35	83.8%	30	0.3%	19	14.5%	26	12.1%	20
Panama City, FL	3,592,699	56	79.8%	34	0.1%	42	14.5%	27	10.8%	28
New York-Newark-Jersey City, NY-NJ-PA	389,971,283	1	85.4%	27	0.1%	40	14.4%	28	7.6%	38
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	35,561,772	21	72.8%	45	0.4%	14	14.4%	29	13.3%	19
Jacksonville, NC	24,365,009	29	69.7%	48	0.7%	9	14.2%	30	5.1%	46

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Exposure Metrics under Current Sea Level						Exposure Increase Metrics under Medium Sea Level Rise			
Metropolitan Statistical Area Title (Note 1)	Total Annual Losses (Note 2)	Total Annual Losses Rank (Note 3)	Percent of Losses Uninsured (Note 4)	Percent of Losses Uninsured Rank (Note 5)	AAL to Income Ratio (Note 6)	AAL to Income Ratio Rank (Note 7)	Percent Increase in Total Loss (Note 8)	Percent Increase in Total Loss Rank (Note 9)	Percent Increase in 500 Year Return Period Loss (Note 10)	Percent Increase in 500 Year Return Period Loss Rank (Note 11)
Crestview-Fort Walton Beach-Destin, FL	8,616,116	46	79.2%	35	0.1%	38	13.7%	31	11.5%	22
Tampa-St. Petersburg-Clearwater, FL	136,837,328	7	66.9%	53	0.3%	22	13.4%	32	11.1%	23
Wilmington, NC	23,194,192	30	84.0%	29	0.4%	15	13.3%	33	9.8%	32
Palm Bay-Melbourne-Titusville, FL	27,107,739	24	89.9%	11	0.2%	25	13.0%	34	9.1%	34
Daphne-Fairhope-Foley, AL	13,349,807	41	88.4%	18	0.3%	18	12.6%	35	10.1%	31
Norwich-New London, CT	6,890,794	49	82.6%	31	0.1%	47	12.2%	36	14.7%	15
Baton Rouge, LA	19,909,601	33	64.6%	56	0.1%	35	12.0%	37	8.8%	36
Homosassa Springs, FL	13,655,529	40	68.3%	49	0.6%	11	11.8%	38	5.6%	41
New Haven-Milford, CT	25,364,184	27	87.1%	21	0.1%	37	11.6%	39	9.7%	33
New Orleans-Metairie, LA	258,015,593	3	74.5%	43	1.3%	5	11.4%	40	5.2%	44
Brownsville-Harlingen, TX	5,767,671	51	89.4%	14	0.2%	33	11.1%	41	4.1%	50
Port St. Lucie, FL	22,742,400	31	78.3%	36	0.2%	23	11.0%	42	5.3%	43
Dover, DE	2,120,168	59	88.8%	15	0.1%	52	10.9%	43	0.9%	55
Mobile, AL	14,267,187	38	88.4%	19	0.2%	27	10.6%	44	7.6%	39
Portland-South Portland, ME	24,652,928	28	93.7%	4	0.2%	29	10.6%	45	9.0%	35
California-Lexington Park, MD	2,072,929	60	73.2%	44	0.1%	55	10.4%	46	5.3%	42
Boston-Cambridge-Newton, MA-NH	87,225,356	9	89.8%	12	0.1%	49	9.5%	47	7.3%	40
Bridgeport-Stamford-Norwalk, CT	39,333,937	20	86.1%	26	0.1%	44	9.1%	48	5.2%	45
Houston-The Woodlands-Sugar Land, TX	212,376,082	4	90.8%	9	0.2%	31	8.7%	49	4.9%	47
Hartford-East Hartford-Middletown, CT	16,774,956	36	88.3%	20	0.1%	56	6.9%	50	4.4%	48
Hammond, LA	2,655,297	57	61.7%	60	0.2%	32	6.3%	51	2.4%	52
Pensacola-Ferry Pass-Brent, FL	10,185,699	45	76.7%	42	0.1%	46	6.0%	52	4.1%	49
Tallahassee, FL	5,487,041	53	62.7%	59	0.1%	48	5.6%	53	3.6%	51
Baltimore-Columbia-Towson, MD	18,761,905	34	89.7%	13	0.0%	63	3.5%	54	1.6%	53
Providence-Warwick, RI-MA	11,708,224	42	86.9%	23	0.0%	59	3.5%	55	1.5%	54
Gainesville, FL	6,245,276	50	80.8%	33	0.2%	34	2.5%	56	0.4%	56
Washington-Arlington-Alexandria, DC-VA-MD-WV	55,383,798	17	88.6%	17	0.0%	61	2.5%	57	0.1%	57
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	74,242,296	10	91.6%	7	0.1%	57	0.6%	58	0.0%	58
Orlando-Kissimmee-Sanford, FL	28,564,743	23	86.6%	24	0.1%	53	0.1%	59	0.0%	60
Richmond, VA	10,827,098	44	85.2%	28	0.0%	60	0.1%	60	0.0%	59
Kingston, NY	5,531,774	52	77.9%	39	0.1%	36	0.0%	61	0.0%	61
Bangor, ME	743,674	62	100.0%	1	0.0%	62	0.0%	62	0.0%	63
Greenville, NC	2,244,732	58	92.8%	6	0.1%	50	0.0%	63	0.0%	62

Notes:
1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Column (2) = Exhibit 8, Column (8)
3. Rank based on total annual losses for MSAs with storm surge exposure.
4. Column (4) = Exhibit 8, Column (9). Insured and Uninsured Losses are based on estimates of NFIP take-up rates and coverages.
5. Rank based on percent of losses uninsured for MSAs with storm surge exposure.
6. Column (6) = Exhibit 13, Column (3)
7. Rank based AAL to income ratio for MSAs with storm surge exposure.
8. Column (8) = Ratio of inland flood and storm surge losses, medium to current scenario
9. Rank based percent increase in total loss for MSAs with storm surge exposure.
10. Column (10) = Exhibit 14, Column (6)
11. Rank based on percent increase in 500 year return period loss for MSAs with storm surge exposure.

In general, an area will be most affected by sea level rise if both the current exposure and the increase in that exposure are large. Areas with high current exposure but manageable increases in exposure may be able to adapt to sea level rise, assuming current strategies of flood risk management are in place and can scale. MSAs with low current exposure and high increases in exposure may find that implementing new risk-management strategies presents a high value-add proposition at a feasible cost. However, the remaining MSAs may find unique issues due to the incremental change in flood risk.

This study illustrates a significant public policy issue: the protection gap of uninsured flood risk is massive. Our results show that all MSAs have room to greatly increase flood insurance take-up rates and mitigate the disruptive impacts of uninsured flood losses. MSAs that already have moderate to high AAL to income ratios may find this strategy difficult, particularly in the face of high increasing AAL and extreme event losses due to sea level rise as the accompanying affordability and availability of insurance is adversely impacted. Absent an ability or willingness to finance increasingly expensive flood costs, some areas may be subject to strategies or impacts involving relocation of residents. These include managed retreat via policies encouraging or requiring relocation away from more flood-prone areas, and climate gentrification, which occurs as demand for property increases in traditionally lower-income areas that are less flood-prone.

As examples of the above, our results show that the Atlantic City-Hammonton, Ocean City, and Salisbury MSAs all top our lists of exposure increase under medium sea level rise. Atlantic City-Hammonton and Salisbury each have relatively low annual expected losses today both in an absolute context and relative to household incomes. Coupled with a relatively high rate of insured losses, the area may be able to absorb sea level rise impacts more readily than most. Ocean City has high losses relative to the number of residences and incomes. Increasing the insurance take-up rates could be difficult due to affordability issues, and uninsured losses will be more difficult to absorb by homeowners than the other MSAs discussed in this example.

The MSA level results provide an opportunity to assess how the varying degree of flood risk and exposure to sea level rise can pose unique challenges to local region's risk management strategies. They also provide the ability to understand the magnitude of flood risk at a level that can be readily absorbed. However, decisions on managing flood risk will be made from the federal to the local level, and from the insurance industry to the consumer.

4. Projections: Mortgage Default Risks After Catastrophic Flooding

When flood insurance is in place, a portion of incurred losses are absorbed by the NFIP, private flood insurers, and reinsurers. If flood insurance is not in place, state or federal government programs may provide financial disaster assistance, but these programs are not always available and often provide only partial indemnification. To the extent that insurance is not in place or assistance is not available, losses are absorbed by the homeowner, either through out-of-pocket repair costs or through diminishment in home equity if they must finance necessary repairs.

The homeowner is not the only stakeholder in this case. If a homeowner has a mortgage on their residence, diminished value of the collateral property securing it could increase the risk of delinquency or default. As recent flood catastrophes[20] have occurred in non-SFHA areas where flood insurance purchase is exceedingly rare, new attention has been brought to the relationship between the flood insurance gap and potential mortgage credit risk.[21] The lack of flood coverage among U.S. homeowners despite the risk, given the importance of hazard insurance for managing mortgage risk, indicates that there could be a significant degree of exposure to catastrophic flooding that is borne

[20] Hunn, D. (March 30, 2018). Harvey's Floods. Houston Chronicle. Available at: https://www.houstonchronicle.com/news/article/In-Harvey-s-deluge-most-damaged-homes-were-12794820.php

[21] Koning Beals, R. (November 2, 2019). Banks increasingly unload flooded-out mortgages at taxpayer expense. MarketWatch. Available at: https://www.marketwatch.com/story/climate-change-could-impact-your-mortgage-even-if-you-live-nowhere-near-a-coast-2019-09-30

within the U.S. mortgage system. Though it is apparent that this exposure may exist, estimates of its magnitude and potential severity are elusive due to sporadic data on historical catastrophic events, lack of detailed public information, lack of information about historical impacts to household finances after these events, and historically inconsistent government and lender assistance. Since there is no guarantee that ad hoc government and lender assistance programs will be in place in the future, past events may provide poor predictors of future ones, potentially resulting in incomplete estimates of the total exposure of credit losses to extreme flood events.

In this section, simulated property losses from extreme flood events are used to stress test and quantify the potential downstream financial impacts of a natural catastrophe on a mortgage credit risk portfolio, and how these costs could be passed on to lenders, GSEs, mortgage guaranty insurers, and investors. While countrywide diversification mitigates the size of default costs from extreme flood events on a percentage basis, it should be noted that homeowners themselves are unable to diversify nationwide similar to the diversification benefits of a larger mortgage pool.

4.1 POTENTIAL BEARERS OF FLOOD RISK: BEYOND HOMEOWNERS AND INSURERS

In order to understand how the U.S. single-family mortgage industry[22] bears flood risk, an understanding of its market participants is necessary. This section provides an overview of the U.S. mortgage market participants and discusses two representative credit risk transfer (CRT) deals from Freddie Mac.[23]

When a homebuyer borrows money from a lender to purchase a home, the mortgage loan is collateralized by the home being purchased. This means the owner of the mortgage has a lien on the property and can seek recourse by seizing the property if principal and interest are not repaid consistent with the terms of the mortgage. In general, a mortgage has three types of risk: credit risk, interest rate risk, and prepayment risk. The risk that a borrower stops paying their mortgage is known as credit risk, the risk that mortgage principal and interest will not be paid back due to borrower (mortgagor) default. Interest rate risk refers to the risk that mortgage asset prices (that is, the present value of future cash flows from the mortgage loan) fall as interest rates rise. Prepayment risk refers to the risk that the borrower will prepay their mortgage and the investor will receive less interest income than expected (the principal will be returned earlier). In the U.S. mortgage market, each of these risks can be separated and distributed to different investors with different investment strategies and risk appetite.

For credit risk, the mortgage contract allows the lender (mortgagee) to foreclose on and sell the underlying property to recover the amount owed on the loan. Therefore, the value of the underlying property directly impacts the party owning the mortgage asset. Historical data demonstrates that changes in home prices, particularly when they decline, are one of the most significant drivers of mortgage credit risk. During this discussion and analysis, flood risk is tied to mortgage credit risk using the following logic: Flood losses that are uninsured could reduce the value of a property and therefore impact the holder of the mortgage. If a property is affected by a flood, the property could experience a decrease in value, absent subsequent repair. If the borrower stops paying their mortgage, the value of the collateral securing the loan would be worth less than it would be absent the event, and the mortgagee could potentially incur a loss upon sale of the property.

In the U.S. mortgage market, the originator of a given mortgage often sells the mortgage to a third party or obtains mortgage guaranty insurance to protect themselves against credit risk. In order to understand the impact of flood on

[22] Multifamily, 5+ units, is not evaluated in this analysis.
[23] Choice of Freddie Mac CRT deals based on a review of reference pools and structures. Performing this analysis on Fannie Mae CAS/CIRT transactions would likely lead to similar conclusions.

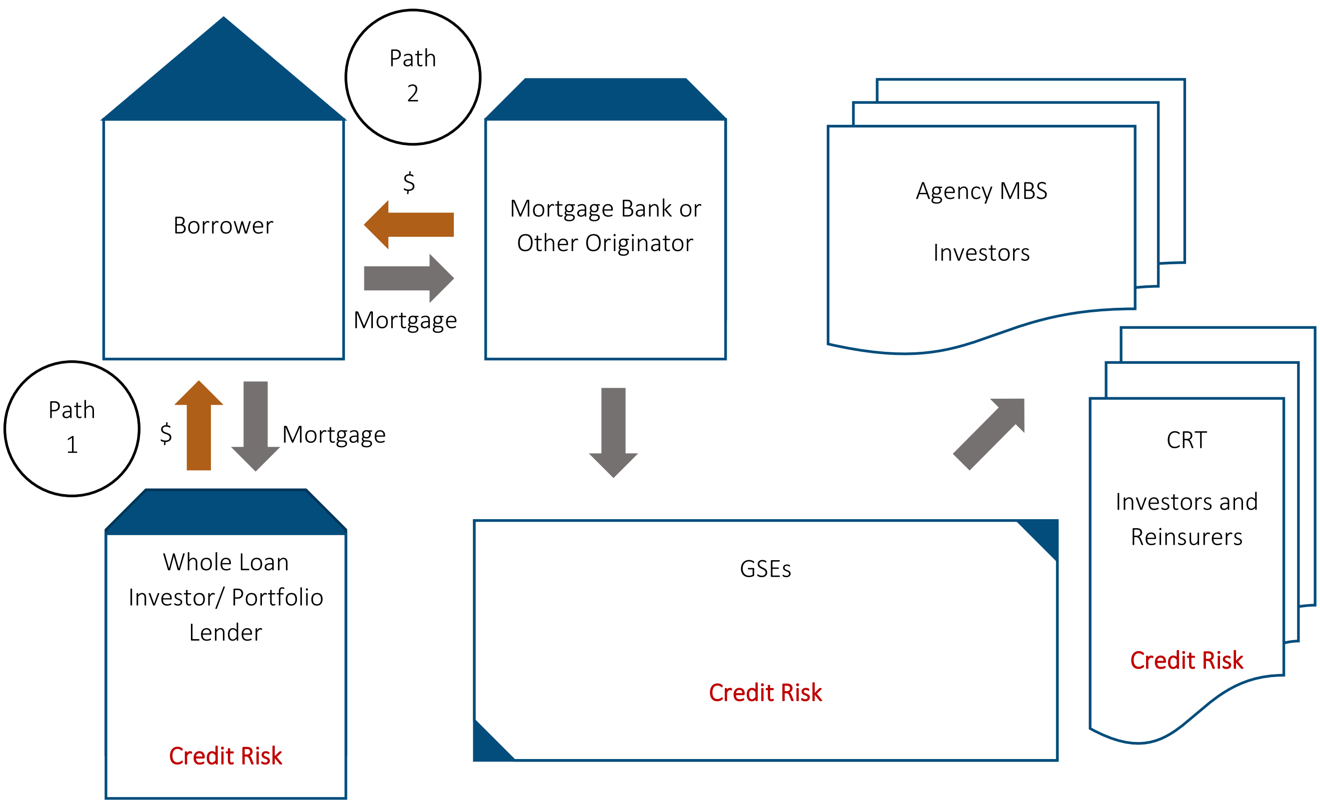
the mortgage market and the ultimate bearers of flood risk, the following section provides a discussion of the holders of mortgage credit risk in the US mortgage market.[24]

Credit Risk Investors in the U.S. Mortgage Market

Mortgages can be originated through a variety of channels. For example, a borrower can go to the physical branch of their bank to obtain a mortgage (retail), a specialized mortgage company that then sells the mortgage to larger entity (correspondent), or a specialized mortgage company that originates the mortgage based on the best terms available from multiple lenders (broker).[25] In all cases, once the loan is originated, the mortgage can be retained by the lender, sold as a whole loan to an investor, or securitized along with other similar assets and sold via a mortgage-backed security (MBS) to investors.

Figure 9 provides a simplified outline of the holders of mortgage credit risk in the U.S. mortgage market.[26]

Figure 9: Illustration of U.S. Mortgage Market



The simplest path for a mortgage to take is to be retained by the lending institution (Path 1 in Figure 9). Under this path, the lending institution collects principal and interest payments from the borrower for the life of the loan. All risks (credit, interest rate, and prepayment) associated with the mortgage remain on the balance sheet of the lending

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[24] Private mortgage guaranty insurers are major holders of U.S. mortgage credit risk. However, their master policies generally stipulate that they will deny a claim where physical damage was the principal cause of the default giving rise to the claim. This includes physical damage caused by floods. As a result, they are not discussed in this analysis.
[25] From the borrower's perspective, retail and correspondent channels are likely similar experiences (e.g., working directly with the institution originating, underwriting, and funding the mortgage).
[26] For the purposes of this paper, Government National Mortgage Association securities and private label mortgage-backed securities are excluded.

institution.[27] As of the first quarter of 2019, balance sheet lending accounted for approximately 30% of the total outstanding mortgage debt.[28]

The common path for a newly originated mortgage in the United States is to be sold to the Federal National Mortgage Association (Fannie Mae) or Freddie Mac (GSEs) and subsequently securitized and sold as agency mortgage-backed securities (agency MBS) to investors (Path 2 in Figure 9). Agency MBS issued by GSEs do not carry credit risk; instead the GSEs bear the credit risk and collect a portion of the loan's interest (known as the guaranty fee) in exchange for a guarantee of timely interest and principal repayment on the agency MBS they issue. As a result, the GSEs historically have borne a large amount of the credit risk on U.S. mortgages (while transferring portions of the interest rate risk).[29] Separate and distinct from GSE agency MBS are securities issued from the Government National Mortgage Association (Ginnie Mae), which are collateralized by mortgages directly insured by government agencies. As of the first quarter of 2019, agency MBS, including Ginnie Mae, accounted for approximately 60% of the total outstanding mortgage debt.[30]

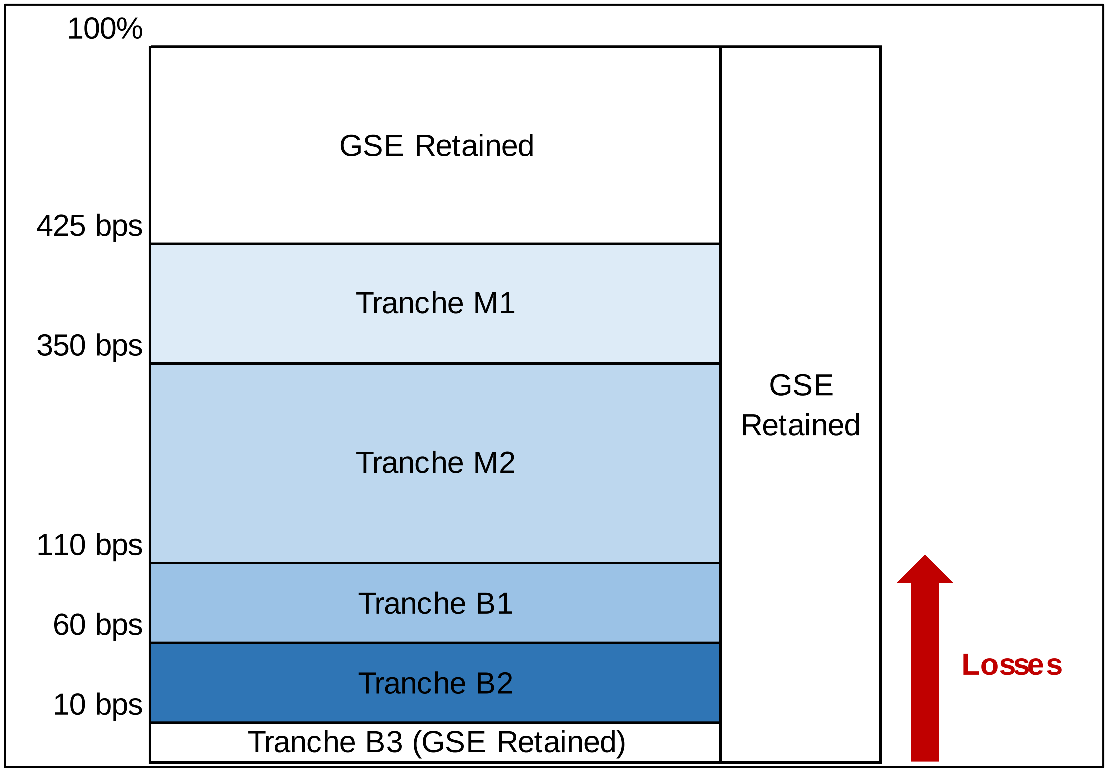
As part of their conservatorship and in an effort to transfer mortgage credit risk to the private market, the GSEs developed debt securities and obtain reinsurance (collectively known as CRT transactions) with market participants. The first of these transactions were offered in 2013. Therefore, as a result of these CRT transactions, the GSEs now share credit risk with many private market participants.

GSE CRT

GSE CRT transfers a portion of the credit risk within pools of similar mortgages owned by the GSEs to investors and reinsurers. The credit risk transfer is achieved by reducing the outstanding principal balance of the CRT securities by the amount of credit losses sustained by the underlying mortgage pool (or in the case of reinsurance, collecting a claim to cover losses in exchange for payment of an insurance premium). GSEs generally transfer risk via structured securities (or reinsurance contacts) where parties invest (reinsure) various tranches of risk. These tranches receive writedowns based on losses exceeding certain thresholds. This concentrates risk in the junior/subordinated tranches of the structures. As a result, mortgage principal losses do not impact all CRT investors/reinsurers proportionally; particular investors and reinsurers in the junior/subordinated tranches of the structures have disproportionately higher exposure to credit risks relative to holders of the senior tranches. Figure 10 illustrates a typical GSE CRT structure.

[27] The lending institution can subsequently purchase mortgage guaranty insurance or other forms of credit enhancement.
[28] Urban Institute, Housing Finance Policy Center (August 2019). Housing Finance at a Glance: A Monthly Chartbook. Available at: https://www.urban.org/sites/default/files/publication/100866/august_chartbook_2019_0.pdf
[29] The GSEs have further protections, mitigating credit risk, not discussed in this paper. Originators represent and warrant that the loans, sold to the GSEs, meet all eligibility and underwriting guidelines. If the loans are found to be ineligible or defective, the agencies have the ability to require the lender to repurchase the defective loans.
[30] The remaining 10% of debt includes second liens and private label mortgage-backed securities.

Figure 10: GSE CRT Structure Example



Since 2013, GSE CRT has transferred the credit risk on more than $3 trillion of mortgages to investors and reinsurers.[31] Today, these structures represent a large and significant portion of the mortgage finance system, and the private market assumes a significant portion of mortgage credit risk. As discussed above, investors in mortgage credit risk could be exposed to flood risk through the collateral underlying the mortgages and supporting the CRT securities or insurance policies. Specifically, flood losses that are uninsured could ultimately impact the holder of mortgage credit risk. If so, investors and reinsurers in the junior or subordinated tranches of the structures could have disproportionately high exposure to losses arising from flood. The next section provides an analysis on how flood losses may impact the holders of mortgage credit risk, including investors participating in the junior/subordinated tranches of the GSE CRT structures.

4.2 METHODOLOGY: CATASTROPHE ANALYTICS FOR HOME LOANS

To develop an initial assessment of how catastrophic losses could impact loan performance, we used output from the KatRisk flood model as input to Milliman's existing M-PIRe loan performance modeling methodology[32] and estimated ranges of collateral loss as a result of mortgage borrower default due to flooding using the following steps:

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[31] Federal Housing Finance Agency (October 2019). The 2019 Strategic Plan for the Conservatorships of Fannie Mae and Freddie Mac. Available at: https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/2019-Strategic-Plan.pdf

[32] Milliman's M-PIRe platform, Mortgage Platform for Investments and Reinsurance, and the technical methodology for modeled mortgage performance is described in the appendix of this report. M-PIRe includes modules to estimate the future performance of mortgage collateral at the loan level using advanced statistical models as well as cash-flow structure models to pass the mortgage collateral forecasts through the capital structure of a given CRT security to estimate investor losses.

1. Select CRT transactions/underlying mortgage pools for analysis

2. Run the loan level underlying mortgage collateral through the KatRisk model to estimate the potential property value decline for each loan as a result of natural disasters under various scenarios

3. Adjust the assumed future house price appreciation scenario for each loan to reflect the property value decline based on modeled flood losses[33]

4. Estimate loan level performance vectors for underlying mortgage pools using adjusted loan-level price appreciation vectors

5. Summarize the output to estimate the potential impact of flood events on mortgage performance (e.g., default frequency increase, loss severity increase, etc.)

6. Run the projected underlying mortgage pools' performance though CRT deal cash-flow waterfall analyses to evaluate the impact of the revised cash flows on investors

7. Summarize the output from the projection of CRT investor and reinsurer losses by tranche

The remainder of this section describes each step in the above analysis in detail for a single event. The event is a 500-year return period flood under current sea levels and takes into account consideration of the benefits of flood insurance. Section 4.3 provides a summary of the analysis for all modeled events, including those considering our selected sea level rise scenarios.

1. Select CRT transactions / underlying mortgage pools for analysis

Two recent issue GSE CRT securities were selected for the population of loans used in this analysis. The two deals selected were STACR/ACIS 2019-DNA2 (low loan to value, or LTV) and STACR/ACIS 2019-HQA2 (high LTV). These transactions are representative of GSE loan acquisitions, and are issued by Freddie Mac.[34] The low-LTV deal contains loans with an initial loan-to-value ratio greater than 60% and less than or equal to 80%. The high-LTV deal contains loans with an initial loan to value ratio greater than 80% and less than or equal to 97%. The GSEs issue low-LTV and high-LTV deals separately, so it was important to run one of each to capture both sections of the mortgage market. The two deals combine to a geographically diverse pool of 168,959 loans with a more than $40 billion unpaid balance (UPB). Table 4 provides some summary statistics of the collateral underlying these transactions.

[33] Home price appreciation is estimated in M-PIRe at the loan level using MSA-level home price index forecasts. Home price appreciation is a key driver of estimated mortgage default risk.
[34] Performing this analysis on Fannie Mae CAS/CIRT transactions would likely lead to similar conclusions. Data availability and a review of recent reference pools informed our choice for this analysis. Freddie Mac STACR/ACIS transactions reference a single pool of loans, while CAS and CIRT transactions reference disparate pools of loans. Using STACR/ACIS reference pools allowed the analysis to be relevant to two CRT executions.

Table 4: Sample Deal Characteristics

	STACR/ACIS 2019-DNA2 (low-LTV)	STACR/ACIS 2019-HQA2 (high-LTV)
Deal Start Date	March 2019	April 2019
Original Number of Loans	86,992	81,967
Total Original Unpaid Balance ($B)	$20.5	$19.5
Weighted Average FICO	750	746
Weighted Average Debt to Income	36.4%	37.4%
Weighted Average Loan to Value	76.5%	92.6%
Weighted Average Interest Rate	4.9%	4.8%

Each transaction is collateralized by mortgages with strong credit profiles having weighted average (weighted by loans' unpaid principal balance) original credit scores of around 750 and weighted average debt-to-income (DTI) ratios slightly higher than 36%. As expected, the loan-to-value ratio varies between each transaction with the low-LTV deal having an initial weighted average LTV of 76.5% and the high-LTV deal having an initial weighted average LTV of 92.6%. The transactions have mortgages with weighted average interest rates of 4.8% to 4.9%.

2. *Run the loan level underlying mortgage collateral through the KatRisk model to estimate the potential property value decline as a result of natural disasters under various scenarios*

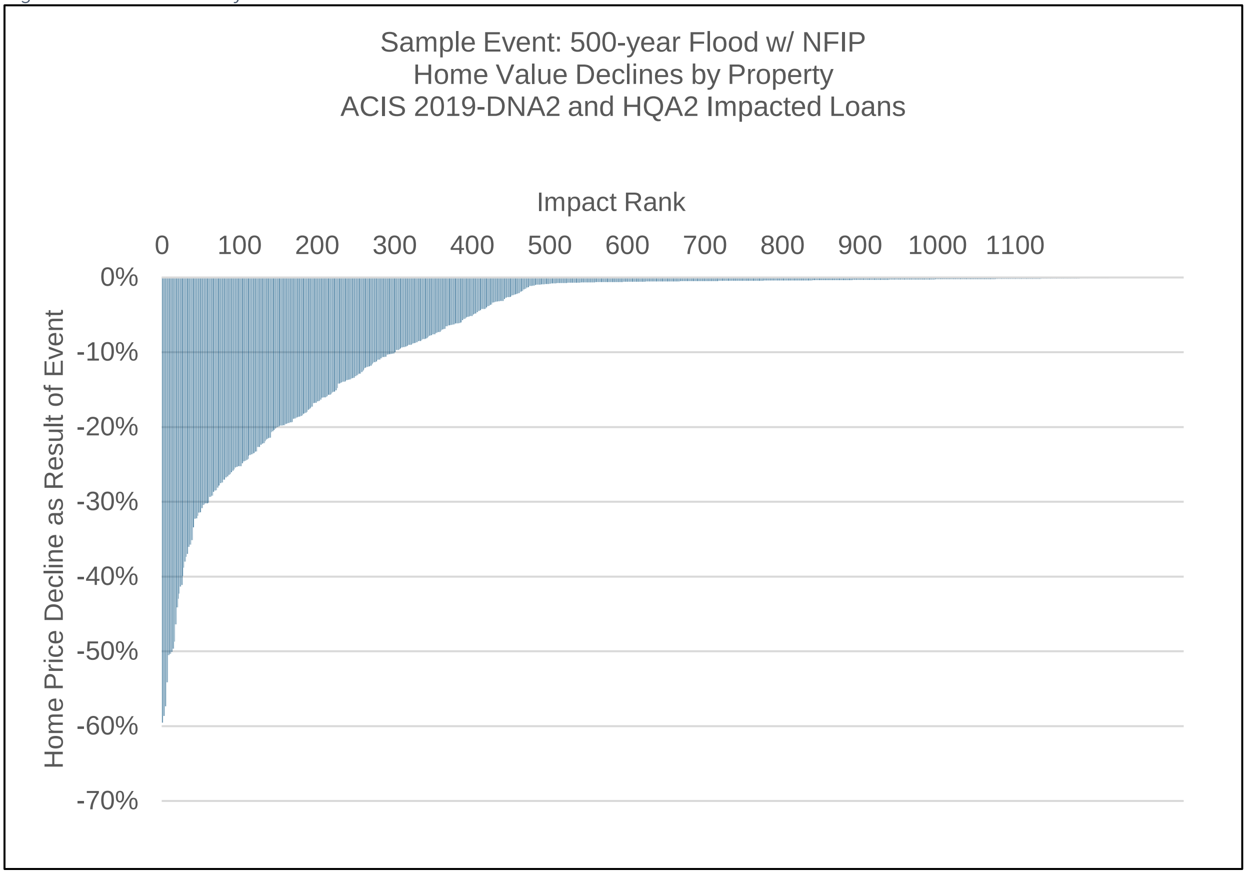
Locations from the market basket were sampled and assigned to loans based on the state, three-digit ZIP code, and MSA for each loan and market basket location. Property value was estimated based on the value in the loan information provided and translated to a building value using data estimates of land share of property value ratios estimated by the Federal Housing Finance Agency as of November 2019.[35] Event-level losses were then generated for each location based on the market basket characteristics and estimated building and property values based on the loan information.

Event-level flood losses were produced with and without consideration for flood insurance benefits, mostly from mandatory purchase requirements. Inside the SFHA, the mandatory purchase requirement was assumed to be adhered to, and homes were assumed to be insured up to the maximum NFIP building limits of $250,000. Outside of the SFHA, take-up rates in Exhibit 7, driven by voluntary purchase of flood insurance, were assumed.

Figure 11 shows the rank order of estimated property value declines after the example event for loans that had a flood loss (impacted loans).

[35] Federal Housing Finance Agency (January 2, 2019). Working Paper 19-01: The Price of Residential Land for Counties, ZIP costs, and Census Tracts in the United States. Available at: https://www.fhfa.gov/PolicyProgramsResearch/Research/Pages/wp1901.aspx

Figure 11: Distribution of Post-Event Home Price Decline



Of the 168,959 loans across the DNA and HQA pools, 1,318 were impacted (0.8% of the total) in the simulated event. Of those that were impacted, the decrease in property value as a result of the event ranges from a max of 59.5% to near 0%. The decrease in property value is determined by deducting the estimated uninsured damage incurred on the building as a result of the event divided by the original value of the property. The weighted average home value decline is 6.1% within the impacted areas.

Despite the potentially material impact on individual properties, the weighted average impact of a given event on the value of all the properties underlying the pool of mortgages is estimated to be a modest decline of 0.05%. The impact is relatively small at the pool level because the pool is geographically diverse and fewer than 1.0% of the loans are impacted by this simulated event.

3. *Adjust the assumed future house price appreciation scenario for each loan to reflect the property value decline based on modeled flood losses*

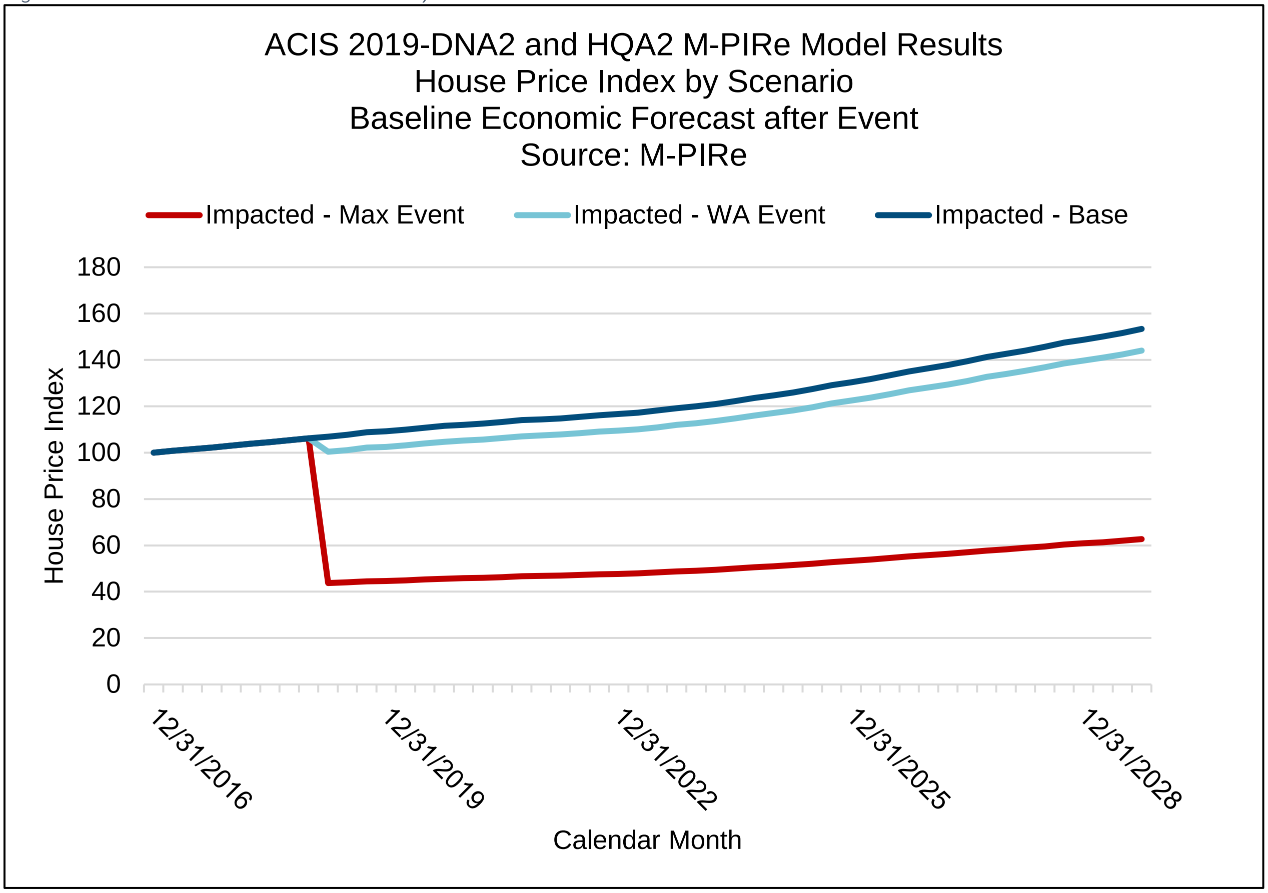
To estimate the impact that flood events have on mortgage performance, the loan-level simulated decrease in property value is assumed to occur at time 0 and is treated as a "shock" to the home price. For example, if the original property value is $100,000 at time 0 and the assumed home price appreciation is 3% per year for the next five years, the model estimates the property value to be $100,000 at time 0, $103,000 at time 1, $106,090 at time 2, etc. If the impact to the value of property as a result of the flood is estimated at 20% at time 0, then the value of the property is estimated to be $80,000 at time 0, $82,400 at time 1, $84,872 at time 2, etc.

Historical data and mortgage performance models indicate that mortgage default events are heavily correlated with changes in home prices. Specifically, declines in home values result in increased mortgage defaults and severity rates. The below methodology will rely on these relationships to estimate how mortgages perform following an event.

Due to the wide range of shocks stemming from the flood event, the methodology must capture changes in property values at the loan level. Applying a weighted average 6.1% shock to the entire impacted region is not equivalent to capturing the full distribution of shocks across the individual loans. The relationship between home price declines and mortgage defaults is not linear due to optionality of mortgages, borrower resilience to small changes in house prices, and borrower incentives. If 100 loans all have a 0.5% negative house price shock, the results will not be equivalent to 99 loans having a 0% shock and one loan having a 50% shock.

Figure 12 shows the range of the unadjusted house price index path versus the max decline house price index path, along with the weighted average (WA) path.

Figure 12: Modeled House Price Forecasts by Scenario



The three paths shown in Figure 12 display the variance in the distribution of property value declines as a result of the example event.

4. *Estimate loan level performance vectors for underlying mortgage pools using adjusted loan-level price appreciation vectors*

Loan-level performance vectors were estimated as a function of each loan's underwriting characteristics (e.g., original FICO score, original loan-to-value ratio, debt-to-income ratio, and others) and underlying property value, as measured by MSA-level home price indices.

In order to estimate the impact of the house price shock due to a flood event, each loan was run through two separate iterations of the mortgage performance model in M-PIRe. The first run was the unadjusted baseline run for all loans in the pool. This provides a view of the model's baseline projected performance under a baseline economic scenario.

There were no shocks to house prices applied in this iteration, and each loan received a forecasted house price appreciation path equal to Moody's baseline forecast for the property's MSA (or state if a property does not fall in an MSA).

The second iteration of the model output was performed with the flood-event shocks applied to the loan-level house price appreciation. After the shocks to house prices were applied, each loan reverted back to receiving a forecasted house price appreciation path equal to Moody's baseline forecast for the property's MSA (or state if a property does not fall in an MSA). This results in an apples-to-apples comparison to the baseline unadjusted run for the goal of distilling out the impact of the flood events.

In this analysis, all loans begin as performing at inception of the CRT transaction. In the model, the estimated drop in the value of the home will be an immediate negative impact to borrower equity. This will in turn result in increased delinquencies, foreclosure rates, and severity rates for impacted loans.

One aspect of the mortgage performance model that was altered for the performance of this analysis was the mortgage guaranty insurance proceeds module. In general, for the GSEs to purchase a loan with an LTV greater than 80%, a mortgage guaranty insurance policy must be purchased on that loan (either by the borrower or the lender). The borrower or lender pays the mortgage guaranty insurer (MI) a premium and in exchange the MI will reimburse the mortgage holder (investor) for a portion of the lost principal in the event of borrower default.

In MI's master policy documents, a document that outlines the terms and conditions under which the MI will cover a loss resulting from a borrower default, there is generally a clause stating that the MI will not be liable for any losses resulting from physical property damage, excluding normal wear and tear. Many MIs explicitly state flood as one of the causes of damage that they will not be liable for. As a result, it is likely that under any of the events contemplated in this analysis, the MIs covering the loans in the impacted region would deny the claims on these properties. This would result in even higher losses as a result of the event.

To capture this potential outcome, the mortgage guaranty insurance proceeds module (which nets out the MI proceeds received on high-LTV loans from the loss severity) was overridden—for just those loans projected to incur flood damage due to the event—to not reflect any benefit from MI coverage.

5. *Summarize the output to estimate the potential impact of flood events on mortgage performance*

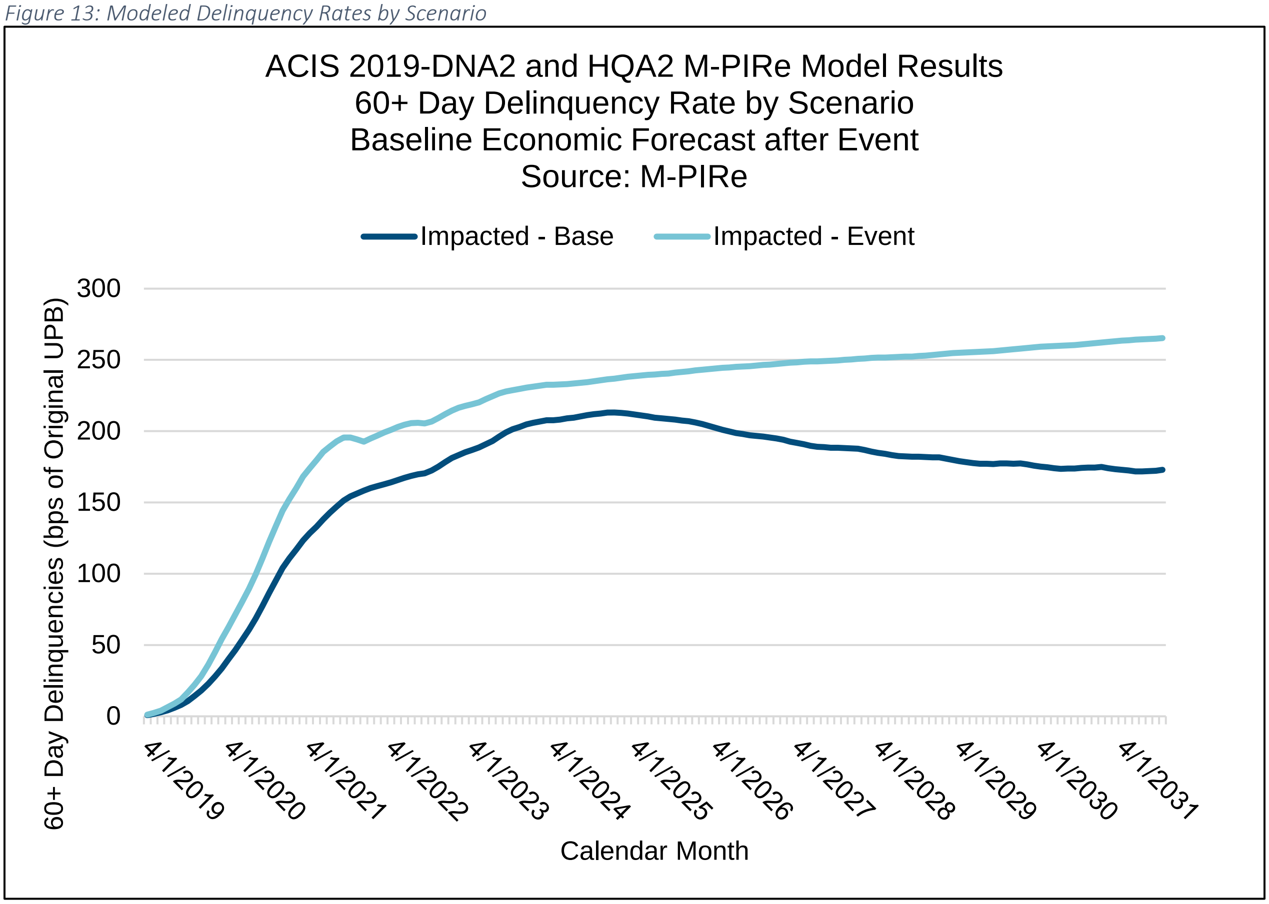
The analysis above results in projections of future collateral performance and investor cash flows over the life of the collateral. As the collateral for these two deals consists of almost 170,000 individual mortgages, the results need to be summarized down to standard performance metrics used to evaluate mortgage performance. Table 5 provides a description of the metrics used in this analysis.

Table 5: Mortgage Model Metrics

Metric	Description
60+ Delinquency Rate	The percent of active loans that are two or more payments delinquent. Loans that are delinquent are leading indicators of future losses, and higher delinquency rates indicate increased credit risk.
Conditional Default Rate (CDR)	The percent of active loans estimated to default in a given period. CDRs are typically annualized, so if the model expects one loan out of 100 loans to default in a given month, the CDR would be 12% (12% = 1 / 100 * 12).
Loss Rate	Total loss amount from default events divided by the original pool balance.

The model results estimate that immediately following an event, the 60+ day delinquency rate begins to rise for loans impacted by the event. The M-PIRe mortgage performance model takes the equity position, and change in equity position, of the borrower at each forecast quarter as a predictor variable. For loans impacted by the event, the equity position experiences a potentially significant decrease, putting upward pressure on delinquency rates. Figure 13 shows that the event causes the estimated 60+ day delinquency rate of the impacted region to be more than 20% higher than it would be absent the event.

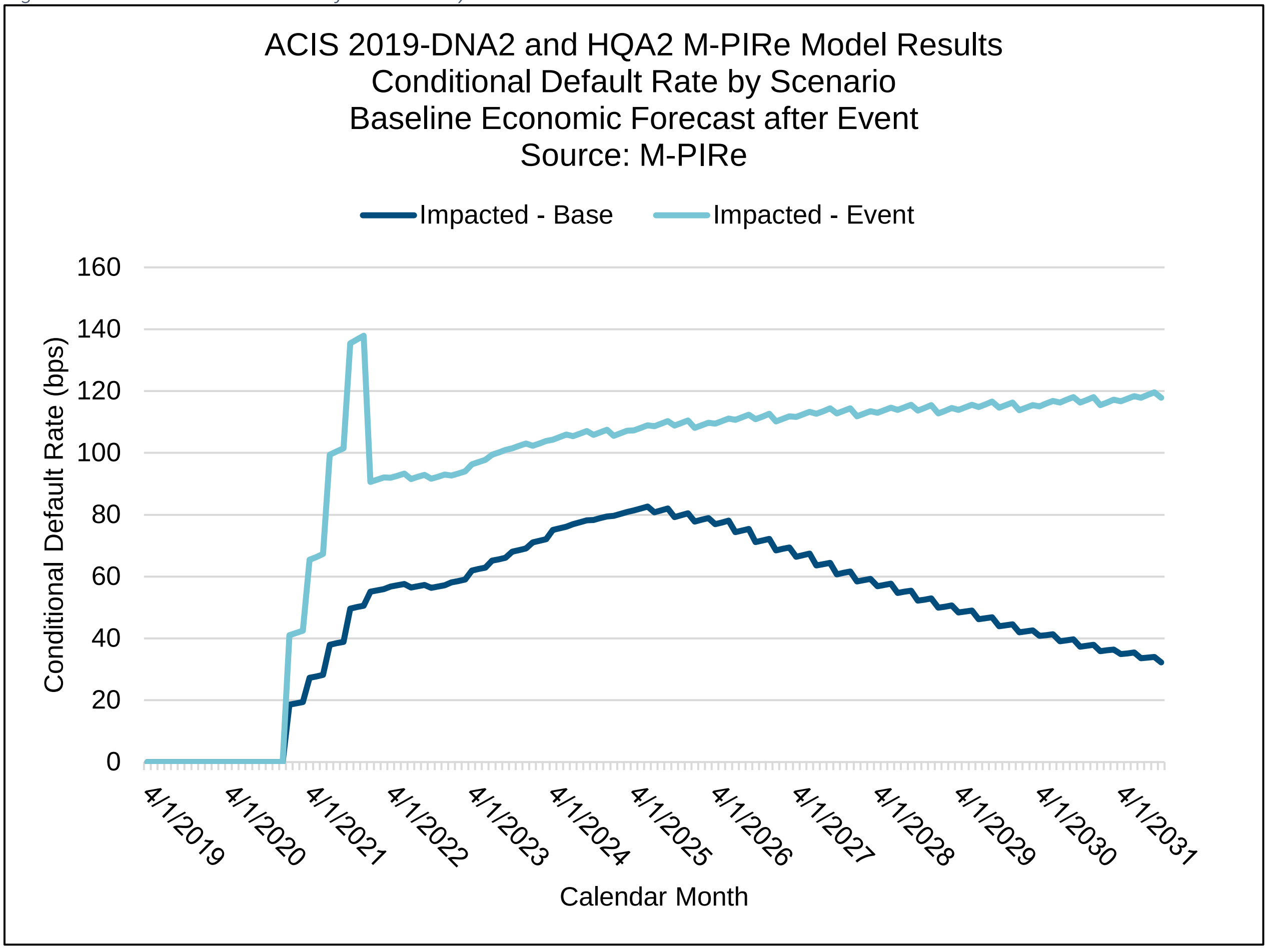
Figure 13: Modeled Delinquency Rates by Scenario



In the analysis, the event takes place in 2Q 2019, and it takes approximately 18 months for the event to lead to mortgage defaults (e.g., a foreclosure, short sale, or other credit event). Generally, the loan servicer will work with the borrower to avoid default, extending the timeline of an ultimate default. If default is inevitable, it still takes approximately 12+ months from delinquency to claim for the foreclosure process to complete. This timeline varies based on state level requirements for foreclosure proceedings.

The flood event causes the conditional default rate (CDR) to spike in 2021, as many of the impacted borrowers 18 months earlier are not estimated to recover from the event; the CRT comparison is shown on Figure 14. In late 2021, the CDR is more than three times greater than it would have been absent the event.

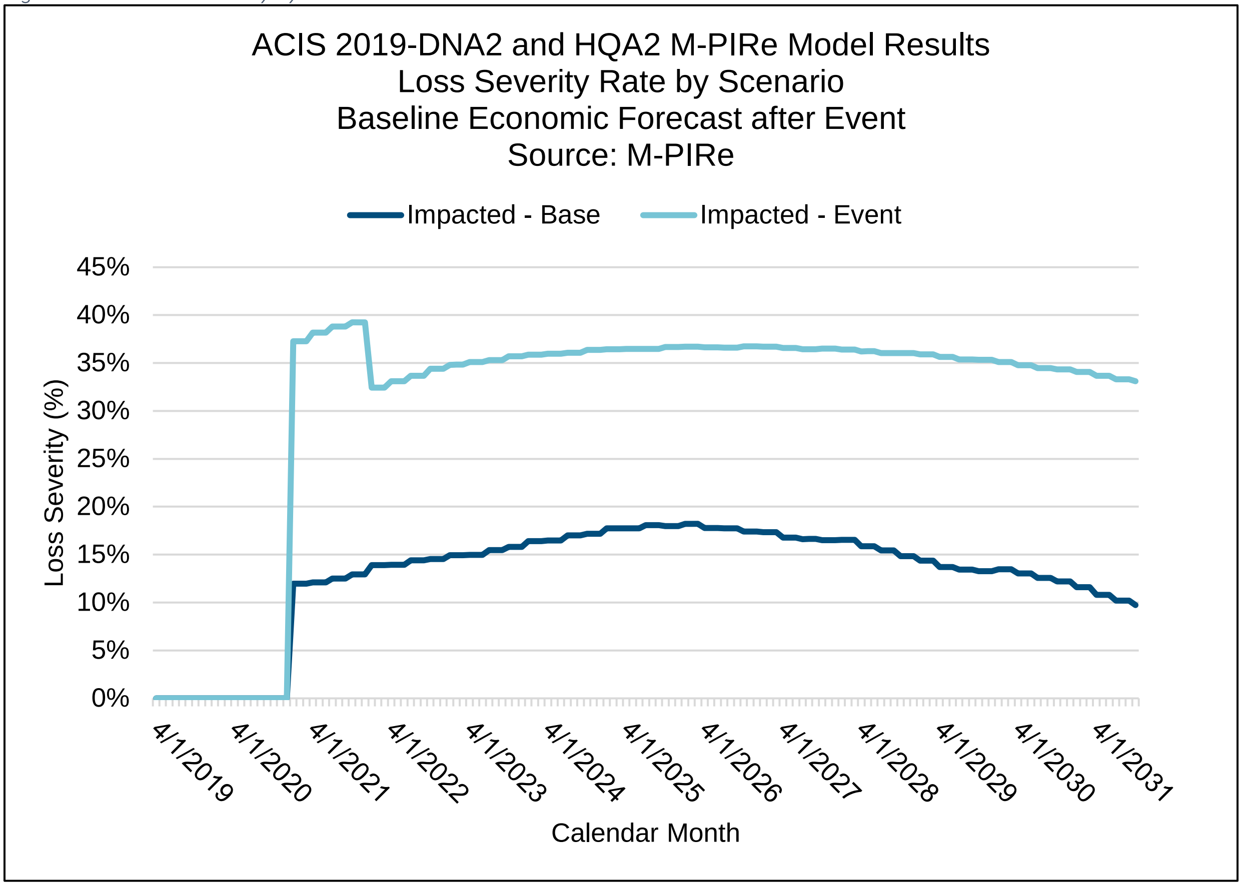
Figure 14: Modeled Conditional Default Rates by Scenario



Compounding the event's impact on homeowners' inability or unwillingness to pay their mortgage, the loss severity (shortfall as a percent of the loan's unpaid principal balance) of those mortgages that default is also sharply increased due to the estimated decline in the value of the underlying property.

Figure 15 provides a visual of the model forecast loss severity.

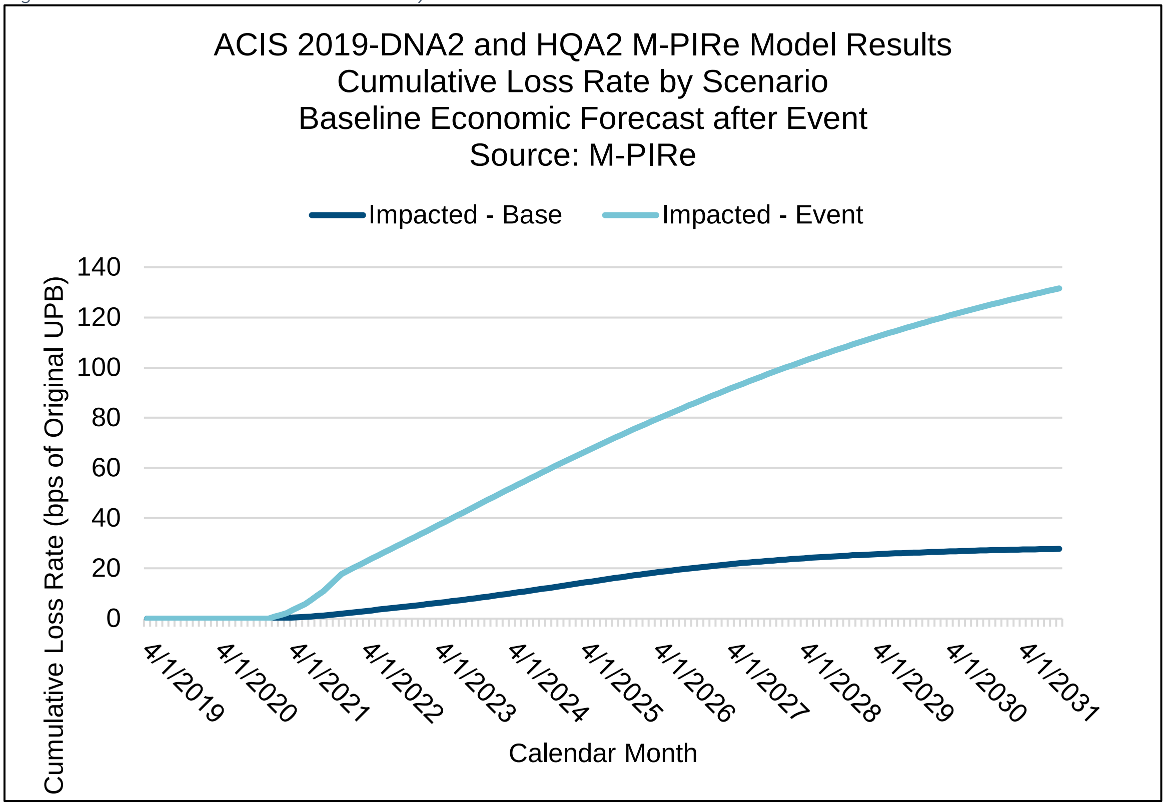
Figure 15: Modeled Severity by Scenario



The losses stemming from a loan default are more than two times higher under the event scenario verses absent the event. This impact is rather straightforward. If house prices go down, there is less value to recover when a homeowner is foreclosed on and their home is liquidated. This is further exacerbated due to the lack of mortgage guaranty insurance recoveries on loans with greater than 80% LTV (see above for rationale for removal of MI proceeds).

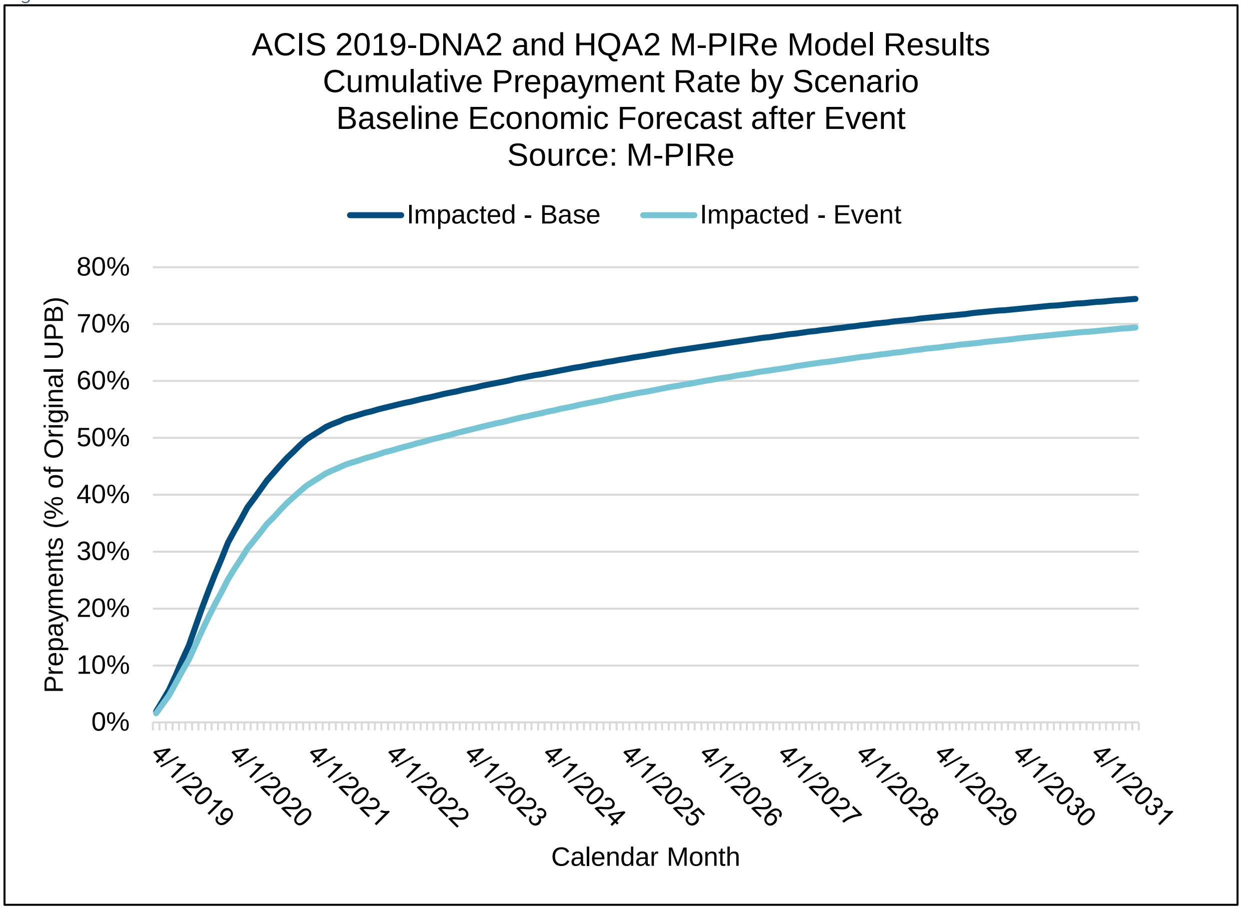
Coupling the increased instances of borrower defaults with the increased loss severity given default, losses develop much more quickly and to a higher ultimate level under the event scenario. Losses within the impacted region are estimated to be more than three times greater under the event scenario than absent the event, as shown in Figure 16.

Figure 16: Modeled Cumulative Loss Rate by Scenario



As the event raises delinquency and adverse outcomes for the borrowers, it also causes borrowers to prepay their loans more slowly, as shown in Figure 17.

Figure 17: Post-Event Economic Forecasts



Throughout the life of the DNA2 and HQA2 reference pools, approximately 5% fewer borrowers are estimated to prepay their mortgage in the impacted area (ultimate prepay rate of 69% versus 74%). Causes of this behavior can include the inability to refinance their loan, decreased mobility, or negative equity in their property. M-PIRe's prepayment model includes variables that capture borrower equity and changes in house prices; as a result of the flood event, equity and house prices decline and translate into a lower forecast prepayment rate, all else equal. However, in reality, borrowers may react to the flood event by vacating damaged properties and/or attempting to move away from the impacted area, thus mitigating or reversing the expected drop in prepayments. Such reactions to flood events are not contemplated in this analysis.

6. *Run the projected underlying mortgage pools' performance though CRT deal cash-flow waterfalls to evaluate the impact of the revised cash flows on investors*

The above analysis discusses the impact of the flood event on the underlying collateral. The credit risk of these transactions was offered to the private market through CRT bonds and reinsurance treaties. Table 6 provides a description of the credit risk for each execution. The table lists the tranches and associated credit enhancement for each. The credit enhancement represents the amount of credit losses required before a given tranche incurs losses. For example, for ACIS 2019-DNA2, the B-1H tranche has 0.60% credit enhancement. This means that if the cumulative loss rate on the transaction (the sum of credit losses divided by the original unpaid balance of the mortgage pool) exceeds 0.60%, then the B-1H tranche will start to incur losses. The B-1H tranche will incur losses until losses exceed 1.10%, at which time the B-1H tranche would be fully exhausted and the M-2H tranche would start to incur losses.

Table 6: Credit Enhancement by Tranche

	Credit Enhancement by Tranche			
Tranche	ACIS 2019-DNA2	ACIS 2019-HQA2	STACR 2019-DNA2	STACR 2019-HQA2
Retained	4.25%	4.50%	4.25%	4.50%
M-1(H)	3.50%	3.50%	3.50%	3.50%
M-2(H)	1.10%	1.50%	1.10%	1.50%
B-1(H)	0.60%	0.60%	0.60%	0.60%
B-2(H)	0.10%	0.10%	0.10%	0.10%
B-3(H)	0.00%	0.00%	0.00%	0.00%

This waterfall is programmed into M-PIRe for the entire population of possible CRT transactions. The above modeled cash flows were run through the cash-flow library to estimate investor cash flows.

STACR tranches can be further broken down into A and B classes, as shown in Table 7. For example, B-2B has 0.10% initial credit enhancement, and B-2A has 0.35% initial credit enhancement. Class B-2B is the class of notes closest to the first loss position (directly behind the retained B-3 tranche). When analyzing how losses due to specific flood events can translate into disproportionately higher losses for investors in riskier classes of notes, we focus on the B-2B tranche.

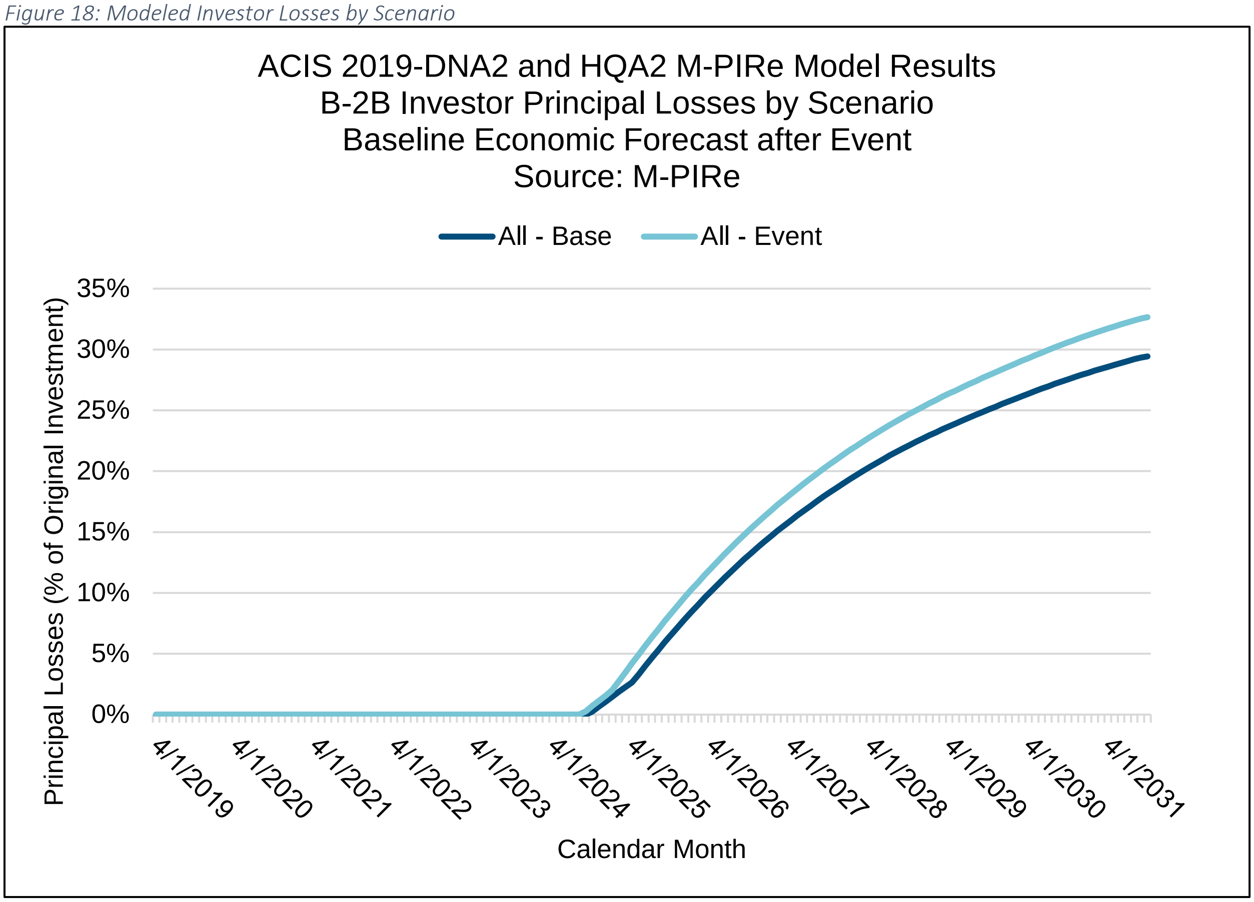
Table 7: Credit Enhancement by Tranche – STACR A and B Tranches

	Credit Enhancement by Tranche	
Tranche	STACR 2019-DNA2	STACR 2019-HQA2
Retained	4.25%	4.50%
M-1	3.50%	3.50%
M-2A	2.30%	2.50%
M-2B	1.10%	1.50%
B-1A	0.85%	1.05%
B-1B	0.60%	0.60%
B-2A	0.35%	0.35%
B-2B	0.10%	0.10%
B-3	0.00%	0.00%

7. *Summarize projection of CRT losses by tranche to estimate the impact from the flood event*

From the above analysis, the impact on the pool level losses as a result of the event is estimated to be approximately one basis point for the sample event. The baseline scenario estimates loss rates of approximately 17.4 basis points without the event. Therefore, a single event could have a material impact on the credit losses for the more subordinated tranches. Investors in the B-2B tranches for both the high-LTV and low-LTV deals are relying on losses staying below the 10bps B-3 retention level for full principal repayment. As a result, any incremental loss development from a natural disaster will disproportionally impact these investors. The sample event, despite only impacting 0.67% of loans, causes investors to lose more than 3% more of their original principal investment in the B-2 tranche, as shown in Figure 18.

Figure 18: Modeled Investor Losses by Scenario



Excluding the event in the base case scenario, investors in the B-2 tranche are estimated to lose 30% of principal. With the event, investors in the B-2 tranche are estimated to lose 33% of principal.

4.3 RESULTS: CATASTROPHE ANALYTICS FOR HOME LOANS

The above analysis walks through the approach utilized to evaluate the impact flood events can have on mortgage collateral, and the potential impact to bond and reinsurance investors in CRT securities. In total, 16 specific combinations were analyzed to understand the sensitivity of mortgage impacts to flood event severity, sea levels, and flood insurance/mandatory purchase requirements. This section compares results across the alternative scenarios to summarize the range of impact of flood on mortgage collateral performance and investors' credit risk

Six events were selected as the 100- and 500-year return period events based on flood losses for the countrywide market basket, for each of the three sea level scenarios. To isolate the impact of sea level rise on an event, we also analyzed the same 500-year return period event for current sea levels with medium and high sea level rise, adding two additional return period and sea level combinations. Each of these combinations was run with and without considering the benefits of insurance, resulting in our final tally of 16 combinations. When considering the benefits of insurance, we assumed that all homes in the SFHA purchased flood insurance and that those outside the SFHA purchased flood insurance at a rate equal to the statewide average rate outside the SFHA.

Results for impacted regions, defined as loans that incurred at least some flood loss, are shown in Exhibit 3. The house price shocks shown, declines in property value as a result of uninsured building losses, would be substantial under this scenario, which is expected given the extreme nature of this event. The resulting default frequency increase and conditional prepayment rate (CPR) decrease would also be substantial. Even when considering insurance claim payments, we estimate in each scenario that homes with flood damage are at least twice as likely to default on their home post-event.

Exhibit 3: Collateral Performance for Impacted Regions

ACIS 2019-DNA2 and HQA2 Model Results
Collateral Performance
Baseline Economic Forecast after Event
Source: M-PIRe

				Results for Impacted Regions							
Return Period of Flood Losses in Years	**Sea Level Scenario**	**Considers Benefits of Insurance**	**House Price Shock**	WA CPR Base	**WA CPR Shock**	Ultimate Default Freq. Base	**Ultimate Default Freq. Shock**	WA Loss Severity Base	**WA Loss Severity Shock**	Ultimate Loss (bps) Base	**Ultimate Loss (bps) Shock**
100	Current	No	**-22.03%**	15.04%	**11.56%**	1.39%	**8.83%**	16.00%	**55.81%**	22.23	**492.88**
100	Current	Yes	**-9.36%**	15.04%	**13.02%**	1.39%	**4.62%**	16.00%	**47.59%**	22.23	**220.08**
500	Current	No	**-14.22%**	15.53%	**12.20%**	1.78%	**5.84%**	15.62%	**42.90%**	27.79	**250.42**
500	Current	Yes	**-6.15%**	15.53%	**13.57%**	1.78%	**3.67%**	15.62%	**35.90%**	27.79	**131.56**
500 (at Current Sea Levels)	Medium	No	**-16.04%**	15.50%	**11.99%**	1.77%	**6.53%**	15.52%	**44.65%**	27.47	**291.65**
500 (at Current Sea Levels)	Medium	Yes	**-7.07%**	15.50%	**13.44%**	1.77%	**3.99%**	15.52%	**37.69%**	27.47	**150.51**
500 (at Current Sea Levels)	High	No	**-19.08%**	15.50%	**11.72%**	1.75%	**7.76%**	15.47%	**47.41%**	27.02	**367.97**
500 (at Current Sea Levels)	High	Yes	**-8.69%**	15.50%	**13.25%**	1.75%	**4.59%**	15.47%	**40.78%**	27.02	**187.28**
100	Medium	No	**-17.05%**	15.18%	**12.14%**	1.55%	**7.15%**	15.19%	**53.99%**	23.52	**386.02**
100	Medium	Yes	**-7.62%**	15.18%	**13.34%**	1.55%	**4.12%**	15.19%	**46.55%**	23.52	**191.82**
500	Medium	No	**-13.22%**	15.51%	**12.37%**	1.70%	**5.58%**	15.15%	**42.58%**	25.74	**237.76**
500	Medium	Yes	**-5.83%**	15.51%	**13.57%**	1.70%	**3.46%**	15.15%	**34.37%**	25.74	**118.79**
100	High	No	**-30.97%**	14.28%	**13.15%**	2.03%	**20.24%**	10.63%	**76.90%**	21.61	**1,556.31**
100	High	Yes	**-23.72%**	14.28%	**13.12%**	2.03%	**15.78%**	10.63%	**71.21%**	21.61	**1,123.60**
500	High	No	**-41.65%**	16.11%	**11.95%**	2.00%	**22.26%**	15.14%	**68.90%**	30.28	**1,533.49**
500	High	Yes	**-22.76%**	16.11%	**13.01%**	2.00%	**12.62%**	15.14%	**57.53%**	30.28	**725.79**

The above results are calculated on only the impacted region. However, the collateral pool underlying CRT transactions is geographically diverse. Exhibit 4 shows the estimated performance of the entire collateral pool under each scenario. When calculating the impact on the entire collateral pool, the change to average home prices for the entire collateral pool is small, contributing to less than a 1% decrease to home prices for the entire pool across all scenarios.

Exhibit 4: Baseline Economic Performance After Event

ACIS 2019-DNA2 and HQA2 Model Results
Collateral Performance
Baseline Economic Forecast after Event
Source: M-PIRe

				Results for Combined ACIS 2019-2 Pools							
Return Period of Flood Losses in Years	**Sea Level Scenario**	**Considers Benefits of Insurance**	**House Price Shock**	WA CPR Base	**WA CPR Shock**	Ultimate Default Freq. Base	**Ultimate Default Freq. Shock**	WA Loss Severity Base	**WA Loss Severity Shock**	Ultimate Loss (bps) Base	**Ultimate Loss (bps) Shock**
100	Current	No	**-0.09%**	15.05%	**15.03%**	1.36%	**1.39%**	12.79%	**13.91%**	17.39	**19.33**
100	Current	Yes	**-0.04%**	15.05%	**15.04%**	1.36%	**1.37%**	12.79%	**13.26%**	17.39	**18.21**
500	Current	No	**-0.11%**	15.05%	**15.02%**	1.36%	**1.39%**	12.79%	**13.75%**	17.39	**19.13**
500	Current	Yes	**-0.05%**	15.05%	**15.03%**	1.36%	**1.37%**	12.79%	**13.25%**	17.39	**18.20**
500 (at Current Sea Levels)	Medium	No	**-0.13%**	15.05%	**15.02%**	1.36%	**1.40%**	12.79%	**13.98%**	17.39	**19.56**
500 (at Current Sea Levels)	Medium	Yes	**-0.06%**	15.05%	**15.03%**	1.36%	**1.38%**	12.79%	**13.36%**	17.39	**18.40**
500 (at Current Sea Levels)	High	No	**-0.16%**	15.05%	**15.01%**	1.36%	**1.41%**	12.79%	**14.41%**	17.39	**20.35**
500 (at Current Sea Levels)	High	Yes	**-0.07%**	15.05%	**15.03%**	1.36%	**1.38%**	12.79%	**13.57%**	17.39	**18.78**
100	Medium	No	**-0.10%**	15.05%	**15.03%**	1.36%	**1.39%**	12.79%	**14.09%**	17.39	**19.65**
100	Medium	Yes	**-0.05%**	15.05%	**15.04%**	1.36%	**1.38%**	12.79%	**13.41%**	17.39	**18.44**
500	Medium	No	**-0.14%**	15.05%	**15.01%**	1.36%	**1.40%**	12.79%	**14.02%**	17.39	**19.64**
500	Medium	Yes	**-0.06%**	15.05%	**15.03%**	1.36%	**1.38%**	12.79%	**13.34%**	17.39	**18.38**
100	High	No	**-0.13%**	15.05%	**15.05%**	1.36%	**1.44%**	12.79%	**16.73%**	17.39	**24.06**
100	High	Yes	**-0.10%**	15.05%	**15.04%**	1.36%	**1.42%**	12.79%	**15.63%**	17.39	**22.18**
500	High	No	**-0.20%**	15.05%	**15.03%**	1.36%	**1.46%**	12.79%	**17.00%**	17.39	**24.82**
500	High	Yes	**-0.11%**	15.05%	**15.03%**	1.36%	**1.41%**	12.79%	**14.75%**	17.39	**20.83**

Exhibit 5 calculates the percentage increase in credit losses across the scenarios, for both impacted regions and the entire collateral pool.

Exhibit 5: Increase in Credit Losses After Event; Impacted Regions and Combined Pool

ACIS 2019-DNA2 and HQA2 Model Results
Collateral Performance
Baseline Economic Forecast after Event
Source: M-PIRe

			Results for Impacted Regions				Results for Combined ACIS 2019-2 Pools			
				A	B			A	B	
Return Period of Flood Losses in Years	**Sea Level Scenario**	**Considers Benefits of Insurance**	**House Price Shock**	Ultimate Loss (bps) Base	**Ultimate Loss (bps) Shock**	*% Increase = (B-A) / A*	**House Price Shock**	Ultimate Loss (bps) Base	**Ultimate Loss (bps) Shock**	*% Increase = (B-A) / A*
100	Current	No	**-22.03%**	22.23	**492.88**	*2116.7%*	**-0.09%**	17.39	**19.33**	*11.1%*
100	Current	Yes	**-9.36%**	22.23	**220.08**	*889.8%*	**-0.04%**	17.39	**18.21**	*4.7%*
500	Current	No	**-14.22%**	27.79	**250.42**	*801.0%*	**-0.11%**	17.39	**19.13**	*10.0%*
500	Current	Yes	**-6.15%**	27.79	**131.56**	*373.4%*	**-0.05%**	17.39	**18.20**	*4.7%*
500 (at Current Sea Levels)	Medium	No	**-16.04%**	27.47	**291.65**	*961.6%*	**-0.13%**	17.39	**19.56**	*12.4%*
500 (at Current Sea Levels)	Medium	Yes	**-7.07%**	27.47	**150.51**	*447.8%*	**-0.06%**	17.39	**18.40**	*5.8%*
500 (at Current Sea Levels)	High	No	**-19.08%**	27.02	**367.97**	*1261.6%*	**-0.16%**	17.39	**20.35**	*17.0%*
500 (at Current Sea Levels)	High	Yes	**-8.69%**	27.02	**187.28**	*593.0%*	**-0.07%**	17.39	**18.78**	*8.0%*
100	Medium	No	**-17.05%**	23.52	**386.02**	*1541.3%*	**-0.10%**	17.39	**19.65**	*13.0%*
100	Medium	Yes	**-7.62%**	23.52	**191.82**	*715.6%*	**-0.05%**	17.39	**18.44**	*6.0%*
500	Medium	No	**-13.22%**	25.74	**237.76**	*823.6%*	**-0.14%**	17.39	**19.64**	*12.9%*
500	Medium	Yes	**-5.83%**	25.74	**118.79**	*361.4%*	**-0.06%**	17.39	**18.38**	*5.7%*
100	High	No	**-30.97%**	21.61	**1,556.31**	*7103.2%*	**-0.13%**	17.39	**24.06**	*38.3%*
100	High	Yes	**-23.72%**	21.61	**1,123.60**	*5100.4%*	**-0.10%**	17.39	**22.18**	*27.5%*
500	High	No	**-41.65%**	30.28	**1,533.49**	*4965.0%*	**-0.20%**	17.39	**24.82**	*42.7%*
500	High	Yes	**-22.76%**	30.28	**725.79**	*2297.2%*	**-0.11%**	17.39	**20.83**	*19.8%*

Credit losses in impacted regions are an order of magnitude higher post-event. Considering insurance claim payments, the impacted regions for a 100-year event under our high sea level rise scenarios are estimated to be more than 50 times larger post-event.

Across the entire collateral pool, the impacts of mandatory purchase (and voluntary purchase for loans outside the SFHA) can be seen with the reduction in the credit loss increase due to flood losses for an event with and without consideration of the benefits of flood insurance. While current flood insurance purchasing patterns and the mandatory purchase requirement do mitigate the expected impact to credit losses, **model estimates indicate that at least 42% of the expected increase in credit losses due to extreme flood events could remain after considering the benefits of insurance claim payments.**

Following the same 500-year return period event at current sea levels across the medium and high scenarios allows us to isolate the impact of sea level rise on credit losses for a single major catastrophe. We can calculate the extent at which sea level rise impacted credit losses due to flood losses by comparing the credit loss impact of combined results in Exhibit 6. After considering insurance claim payments, the increase in credit losses for the entire collateral pool due to a 500-year return period flood event is 4.7% at current sea levels and is 5.8% in a medium sea level rise scenario. In a high sea level rise scenario, the increase in credit losses is 8.0% for an otherwise similar event. **Thus, credit losses for this event increased by 24% (5.8% impact versus 4.7% impact) and 72% (8.0% impact versus 4.7% impact) using our medium and high sea level rise scenarios, respectively.**

As discussed above, local impacts of some extreme flood events on mortgage defaults could be substantial, with modeled credit losses an order of magnitude higher post-event. **Even considering current insurance purchasing patterns and requirements, estimated credit losses for impacted regions increased between approximately four and 23 times for each of our modeled events.** The incremental credit loss impact estimates, while small on the aggregate pool, could deliver a more significant impact to investors in the subordinate tranches.

Exhibit 6: Increase in Credit Losses After Event; B-2B Bond Performance

ACIS 2019-DNA2 and HQA2 Model Results
B-2B Bond Performance
Baseline Economic Forecast after Event
Source: M-PIRe

			Results for ACIS 2019-DNA2				Results for ACIS 2019-HQA2			
Return Period of Flood Losses in Years	**Sea Level Scenario**	**Considers Benefits of Insurance**	**House Price Shock**	A Ultimate B-2B Principal Loss Base	B **Ultimate B-2B Principal Loss Shock**	*% Increase = (B-A) / A*	**House Price Shock**	A Ultimate B-2B Principal Loss Base	B **Ultimate B-2B Principal Loss Shock**	*% Increase = (B-A) / A*
100	Current	No	**-22.03%**	0.31	**0.38**	*23.7%*	**-0.09%**	0.28	**0.36**	*29.2%*
100	Current	Yes	**-9.36%**	0.31	**0.33**	*8.5%*	**-0.04%**	0.28	**0.32**	*13.9%*
500	Current	No	**-14.22%**	0.31	**0.37**	*20.1%*	**-0.11%**	0.28	**0.36**	*27.5%*
500	Current	Yes	**-6.15%**	0.31	**0.33**	*7.2%*	**-0.05%**	0.28	**0.32**	*15.2%*
500 (at Current Sea Levels)	Medium	No	**-16.04%**	0.31	**0.39**	*25.4%*	**-0.13%**	0.28	**0.38**	*33.8%*
500 (at Current Sea Levels)	Medium	Yes	**-7.07%**	0.31	**0.34**	*9.4%*	**-0.06%**	0.28	**0.33**	*18.5%*
500 (at Current Sea Levels)	High	No	**-19.08%**	0.31	**0.42**	*35.4%*	**-0.16%**	0.28	**0.41**	*45.3%*
500 (at Current Sea Levels)	High	Yes	**-8.69%**	0.31	**0.35**	*13.8%*	**-0.07%**	0.28	**0.35**	*24.6%*
100	Medium	No	**-17.05%**	0.31	**0.40**	*28.9%*	**-0.10%**	0.28	**0.37**	*32.5%*
100	Medium	Yes	**-7.62%**	0.31	**0.35**	*12.3%*	**-0.05%**	0.28	**0.33**	*16.4%*
500	Medium	No	**-13.22%**	0.31	**0.39**	*27.8%*	**-0.14%**	0.28	**0.37**	*33.3%*
500	Medium	Yes	**-5.83%**	0.31	**0.34**	*9.6%*	**-0.06%**	0.28	**0.33**	*17.6%*
100	High	No	**-30.97%**	0.31	**0.47**	*54.3%*	**-0.13%**	0.28	**0.65**	*132.1%*
100	High	Yes	**-23.72%**	0.31	**0.43**	*38.6%*	**-0.10%**	0.28	**0.55**	*95.3%*
500	High	No	**-41.65%**	0.31	**0.62**	*100.9%*	**-0.20%**	0.28	**0.56**	*100.5%*
500	High	Yes	**-22.76%**	0.31	**0.43**	*41.1%*	**-0.11%**	0.28	**0.43**	*52.9%*

Exhibit 6 shows the calculated impact in credit losses for loans of the subordinated B-2B tranche. **For high-LTV loans, even with consideration of flood insurance, extreme flood events could increase principal writedowns by 15% to 95% relative to a baseline scenario without a flood event.** Thus, the relationship between catastrophic and economic concentrations of risk may be important to consider when evaluating and pricing these transactions.

The 100-year and 500-year return period high sea level rise scenarios, unsurprisingly, all have the highest increased credits losses due to flooding. However, when the high sea level rise scenario is run with the 500-year event based on current sea levels, the increased losses isolated due to sea level rise are much smaller. This highlights the variability of mortgage risk due to flood losses. It is likely that the large increase in losses in the 100-year and 500-year high sea level rise scenario are partially a result of the event itself impacting a different geographic area and/or specific loans.

4.4 HISTORICAL RESULTS: 2017 MORTGAGE PERFORMANCE FOLLOWING HURRICANE IRMA

The methodology discussed above relies on existing mortgage models that contain parameters to assess potential cost to mortgage credit holders resulting from home price shocks. This relies on the assumption that home price shocks as a result of a natural catastrophe would result in a similar spike in mortgage delinquencies, foreclosures, and claims as shocks from causes other than natural catastrophes. This assumption may be flawed for a number of reasons. For example, state or federal disaster assistance could mute the impact of underinsurance, or economic circumstances at the time of any catastrophe could be different than those surrounding generic price shocks.

To provide an evaluation of historical mortgage performance following a catastrophe, this section looks at a portfolio of mortgages in Florida following Hurricane Irma, which made landfall as a Category 4 hurricane in the Florida Keys and struck southwestern Florida at Category 3 intensity on September 10, 2017.[36] The combined effect of storm surge, rainfall, and the tide produced inundation levels of three to five feet above ground level for several largely populated cities, with significant flooding in Miami. NOAA estimates the damage caused by Hurricane Irma to be approximately $50 billion,[37] of which insured losses totaled approximately $25 billion.[38]

Sample CRT Deals

The performance on the mortgage collateral underlying two mortgage credit risk transfer deals was analyzed to evaluate the impact Hurricane Irma had on mortgage performance. The two deals used for this analysis are ACIS 2017-3 / STACR 2017-DNA2 and ACIS 2017-5 / STACR 2017-HQA2. Similar to the above analysis, the ACIS 2017-3 deal represents low-LTV loans (i.e., loans originated with a downpayment of 20% or greater) and the ACIS 2017-5 deal represents high-LTV loans (i.e., loans originated with a downpayment of less than 20%). Table 8 provides some summary statistics of these two transactions.

[36] Cangialosi, J.P., Latto, A.S. & Berg, R. (June 30, 2018). Hurricane Irma. National Hurricane Center Tropical Cyclone Report. Available at: https://www.nhc.noaa.gov/data/tcr/AL112017_Irma.pdf
[37] NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2020). https://www.ncdc.noaa.gov/billions/, DOI: 10.25921/stkw-7w73
[38] Insurance Information Institute. Facts + Statistics: Hurricanes. Available at: https://www.iii.org/fact-statistic/facts-statistics-hurricanes

Table 8: Sample 2017 Deals: Characteristics

	ACIS 2017-3 / STACR 2017-DNA2 (low-LTV)	ACIS 2017-5 / STACR 2017-HQA2 (high-LTV)
Deal Start Date	May 2017	July 2017
Original Number of Loans	236,139	129,587
Total Original Unpaid Balance ($B)	$60.7	$31.6
Original Unpaid Balance in All States Excluding Florida ($B)	$57.7	$29.9
Original Unpaid Balance in Florida ($B)	$3.0	$1.7
Percent of Loans in Florida	4.95%	5.32%
Average FICO	751	747
Average Debt to Income	34.7%	35.6%
Average Loan to Value	75.9%	91.6%
Average Interest Rate	3.8%	3.8%

For both deals, loans in Florida comprise between 5% and 6% of the total origination amount. Each transaction is collateralized by mortgages with strong credit profiles having average original credit scores of about 750 and average debt-to-income ratios less than 36%. As expected, the loan-to-value ratio varies between each transaction, with the low-LTV deal having an initial average LTV of 75.9% and the high-LTV deal having an initial average LTV of 91.6%. Both transactions have mortgages with low average interest rates of 3.8%. Based on our review and modeling of these transactions, under a baseline economic scenario and without consideration of any flood events, we would expect relatively low levels of collateral losses in the range of 10 to 20 basis points.

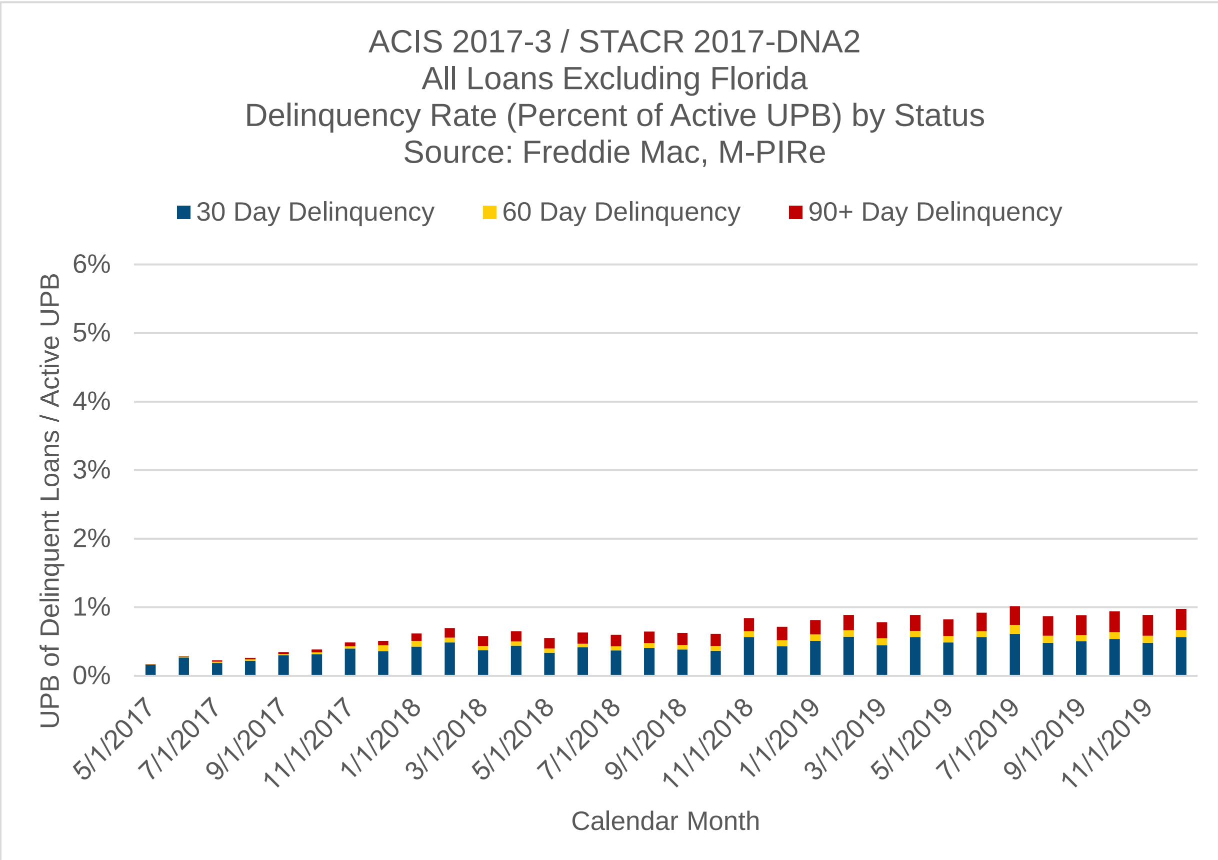
The first payment date for each deal was May 2017 and July 2017 for the low- and high-LTV transactions, respectively. This means the underlying mortgages for each transaction were originated approximately six months prior to the deal start date. Hurricane Irma landed in Florida on September 10, 2017, so the mortgages underlying these two deals were approximately one year seasoned when Hurricane Irma landed.

Delinquency Rates

One early indicator of future losses on mortgage collateral is the status of the loan at a given date. Loans that are 30 days delinquent are more likely to result in a foreclosure or loss to the investor relative to loans that have not missed any payments. Similarly, loans that are 60 days delinquent are more likely to result in a foreclosure or loss to the investor relative to loans that are 30 days delinquent, and so forth. Credit analysts often look at the delinquency development for a portfolio of mortgages as an indication of future losses.

To evaluate the impact of Hurricane Irma on potential future losses, we considered the development of delinquencies before and after the event. Figure 19 shows the unpaid principal balance on loans that are delinquent divided by the unpaid principal balance of all mortgages in the low-LTV transaction by delinquency status (30 days delinquent, 60 days delinquent, and 90+ days delinquent) and calendar month.

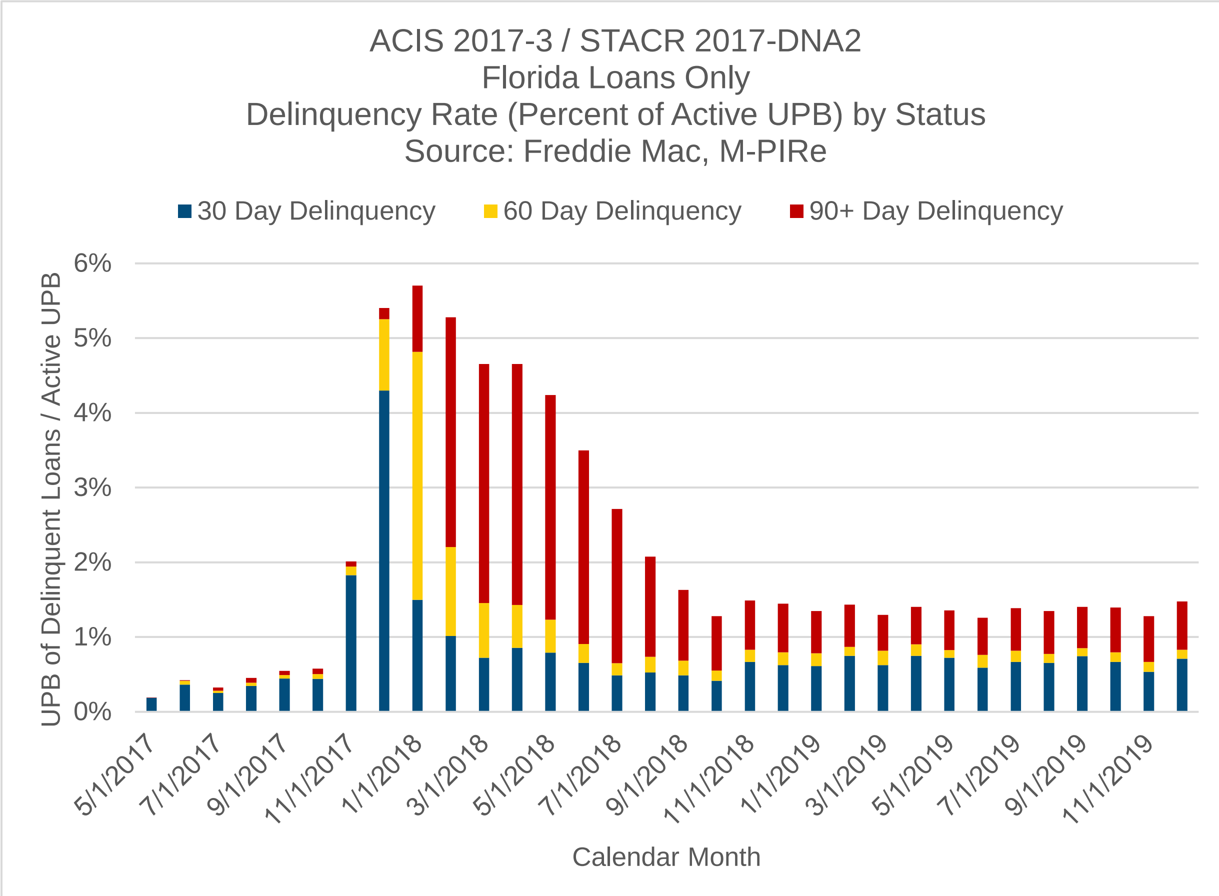
Figure 19: Delinquency Rates: Low LTV Loans Excluding Florida



This figure excludes loans in Florida from the data in order to demonstrate the difference in performance between loans in Florida (i.e., loans potentially impacted by Hurricane Irma) and loans not in Florida (i.e., loans not impact by Hurricane Irma).[39] The figure shows that for the life of this deal from inception through December 2019, the cumulative percent of loans that were delinquent started at 0.2% in the first month and has gradually increased to around 1.0% as of December 2019. The majority of delinquencies are mortgages that are 30 days delinquent, with relatively few loans transitioning into 60 and 90+ day delinquencies. Figure 20 provides the same information, but this figure only includes loans in Florida.

[39] We note that there were additional natural catastrophes during this time, namely Hurricane Harvey and Maria, but either the concentration of loans was not large or the impact on delinquencies was smaller relative to Hurricane Irma. Including or excluding loans impacted by these disasters does not materially change the results of the analysis.

Figure 20: Delinquency Rates: Low-LTV Loans Florida Only



In stark contrast to the non-Florida loans in Figure 19, Figure 20 demonstrates that loans in Florida experienced a spike in delinquencies starting in November 2017, peaking in January 2018 at slightly less than 6%, and gradually declining through October 2018. Significantly, many of the loans that went delinquent quickly transitioned from 30 days delinquent to 60 days delinquent and 90 or more days delinquent. Following October 2018, the percent of loans that are 30- and 60-days delinquent are consistent with the rest of the country, but there still remains an elevated level of defaults that are 90 days delinquent or more in Florida for this transaction.

These results are consistent with the model estimates presented above where a natural disaster results in a shock to the market where the disaster occurs. The shock leads to elevated defaults, which should then result in an increased level of credit losses.

Figure 21 and Figure 22 provide identical information as above but for the high-LTV transaction.

Figure 21: Delinquency Rates: High-LTV Loans Excluding Florida

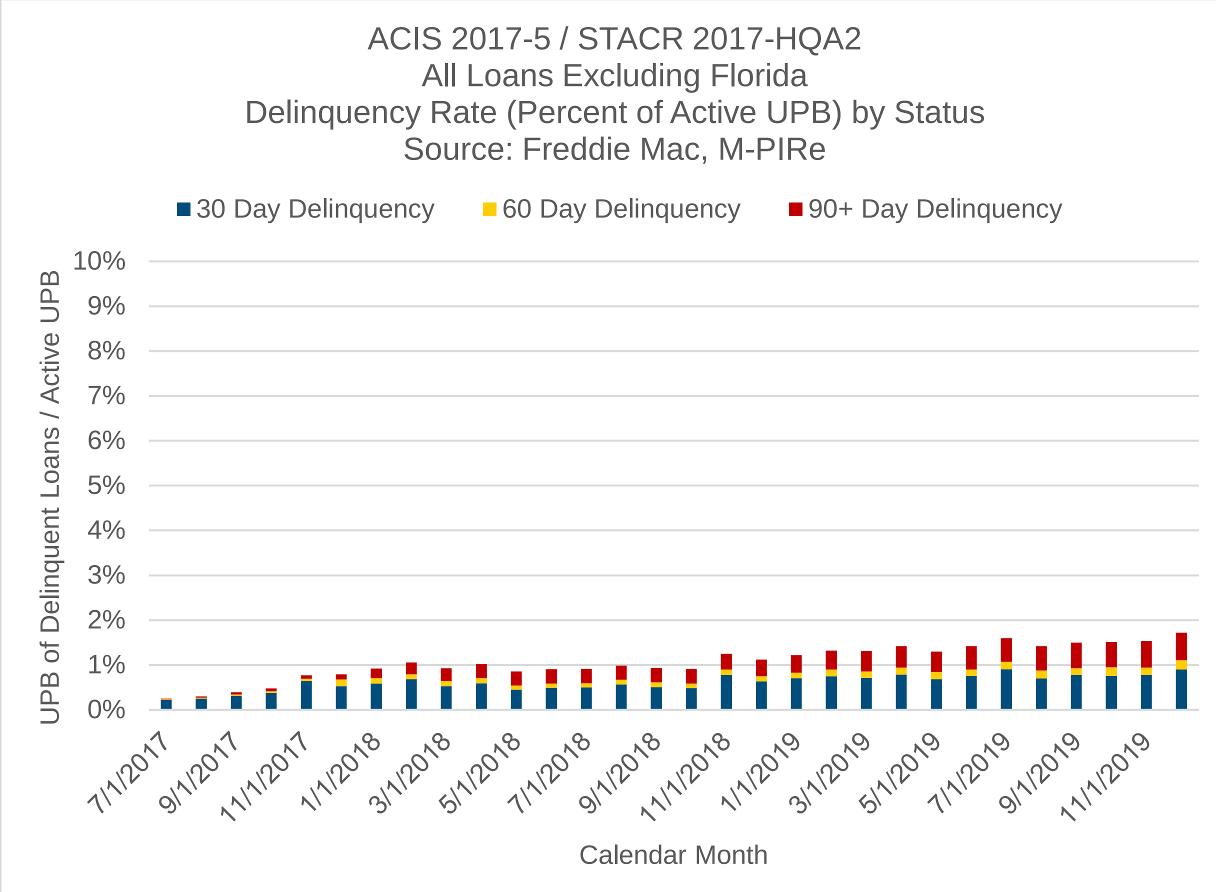
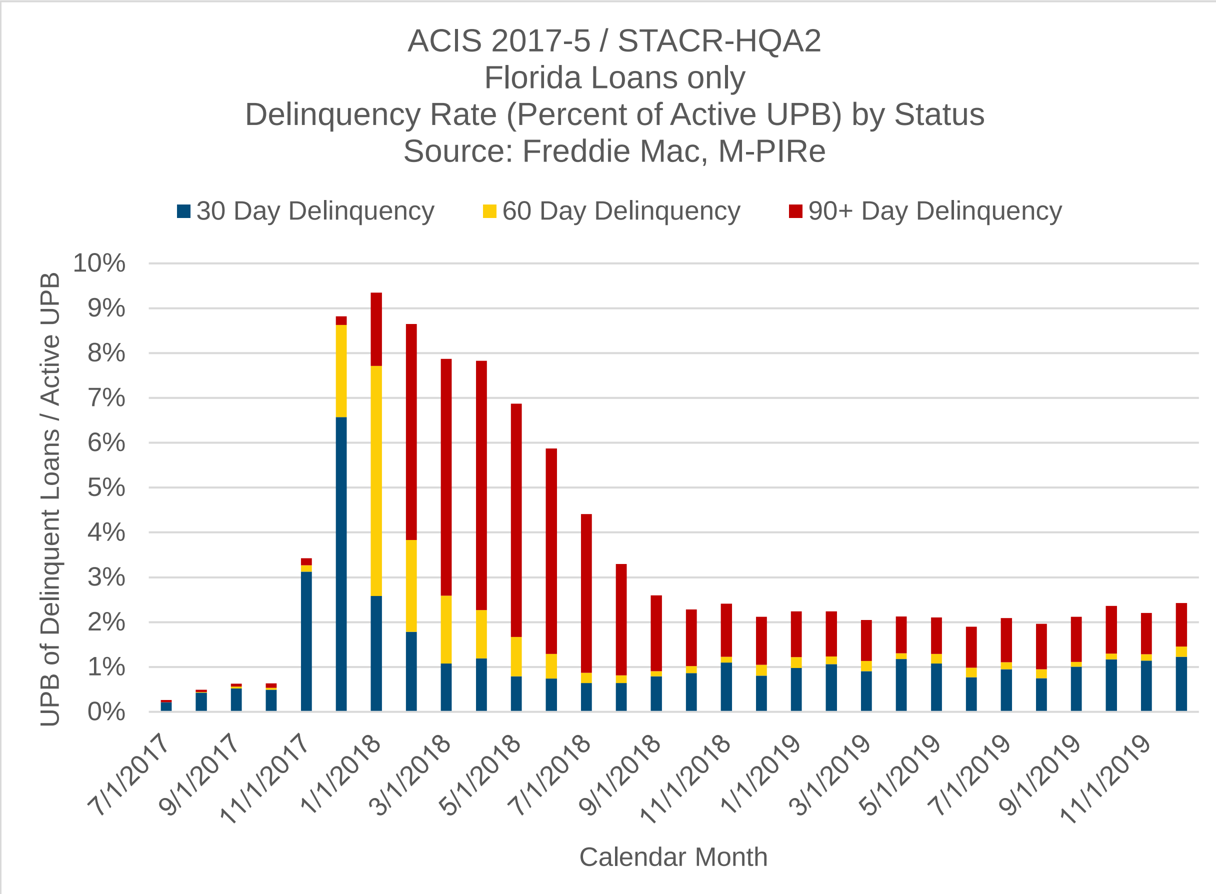


Figure 22: Delinquency Rates: High-LTV Loans Florida Only



For this transaction, the trends and conclusion are the same as the low-LTV transaction, but the level of defaults is greater for the high-LTV transaction, with defaults peaking at more than 9% in January 2018. This result is expected, as the original loan-to-value ratio of a mortgage is a significant predictor of future default rates. Borrowers with larger downpayments have more equity in their property and incentive (and possibly financial resources) to maintain the property, and empirical data confirms that they have lower default rates relative to borrowers with small downpayments.

Typically, loans that are 90 days delinquent transition into foreclosure and result in a loss at a relatively high "roll rate" ranging from 20% to 70%. The roll rate depends on, among other factors, the equity position and creditworthiness of the borrower. Once a loan goes through the foreclosure process, the loss on the mortgage is not the entire unpaid principal balance. The loss is equal to the unpaid principal balance plus delinquent interest and expenses minus the recovery amount collected from selling the property and minus mortgage guaranty insurance payments, if applicable. In recent years, this value, known as the severity, has averaged approximately 15% of the unpaid principal balance. Table 9 estimates the losses that would have been expected using these ranged on the delinquent collateral for each transaction for loans located in Florida. This table represents a rough approximation of losses for demonstrative purposes.

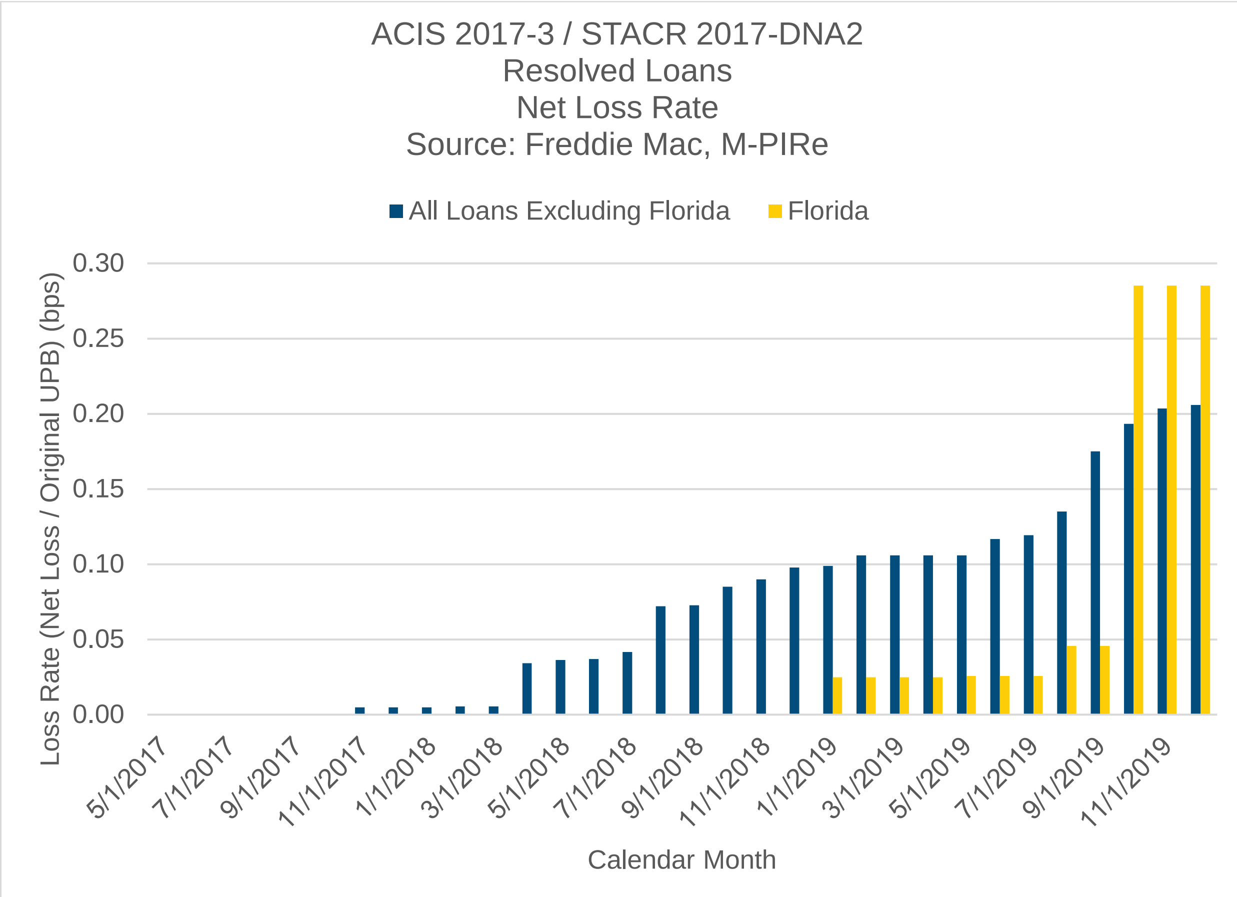
Table 9: Sample 2017 Deals: Expected Performance

	Calculation	ACIS 2017-3 / STACR 2017-DNA2 (low-LTV)	ACIS 2017-5 / STACR 2017-HQA2 (high-LTV)
Peak 90 Day Delinquency Rate	A	3.2%	5.6%
Roll Rate from 90 to Foreclosure	B	20%	20%
Foreclosure	C = A * B	0.64%	1.12%
Severity	D	15%	15%
Expected Losses	E = B * D	0.10%	0.17%

Table 9 uses fairly optimistic estimates for the expected loss, as it only considers 90-day delinquencies (it does not include a provision for 30- or 60-day delinquencies), the roll rate assumption at 20% is on the low-end of the range, and the severity rate at 15% is optimistic, as these loans became delinquent as a result of a natural disaster. Loans impacted by a natural disaster are more likely to have some physical damage that would impact the value of the property, and this is not reflected in the above estimates. Nevertheless, 21 months after the peak 90-day delinquency rate, based on the above analysis, we would have expected at least 10 basis points of loss on the low-LTV transaction and 17 basis points of loss on the high-LTV transaction.

Figure 23 shows the actual cumulative losses through December 2019 for the low-LTV transaction.

Figure 23: Post-Event Low-LTV Net Loss Rates



The losses are segmented between loans in Florida (yellow bars) and loans outside of Florida (blue bars). **Through December 2019, actual cumulative losses on this transaction were less than 0.3 basis points for both populations of loans, significantly less than we would have expected based on the assumption that shocks arising from a catastrophe could be treated the same as generic ones.** Part of the reason for this is because following Hurricane Irma, like other catastrophes, homeowners may receive financial assistance or grace on loan repayment. For example, Freddie Mac offers disaster relief options to borrowers whose loan is owned by it and whose property is located in a presidentially-declared major disaster area. The relief offers suspending foreclosure for a period of 12 months by providing forbearance for up to 12 months following the event, among other benefits, including waiving penalties or late fees and not reporting missed payments to the credit bureaus. Hurricane Irma landed in September 2017, and the disaster relief ended in late 2018. This is likely why Figure 23 does not show any losses for Florida until early 2019, despite the large rate of delinquencies of 90+ days observed throughout 2018. Nevertheless, the comparison between the expectation presented in Table 9 and the observation in Figure 23 does not support the assumption that home price shocks following a natural disaster would have a similar impact on credit risk as other shocks. That is, if home price shocks following a disaster could be expected to behave in this fashion, then this transaction should have incurred significantly more losses relative to actual observations by the end of 2019, which includes 12 months after the expiration of the disaster relief assistance.

Figure 24: Post-Event High-LTV Net Loss Rates

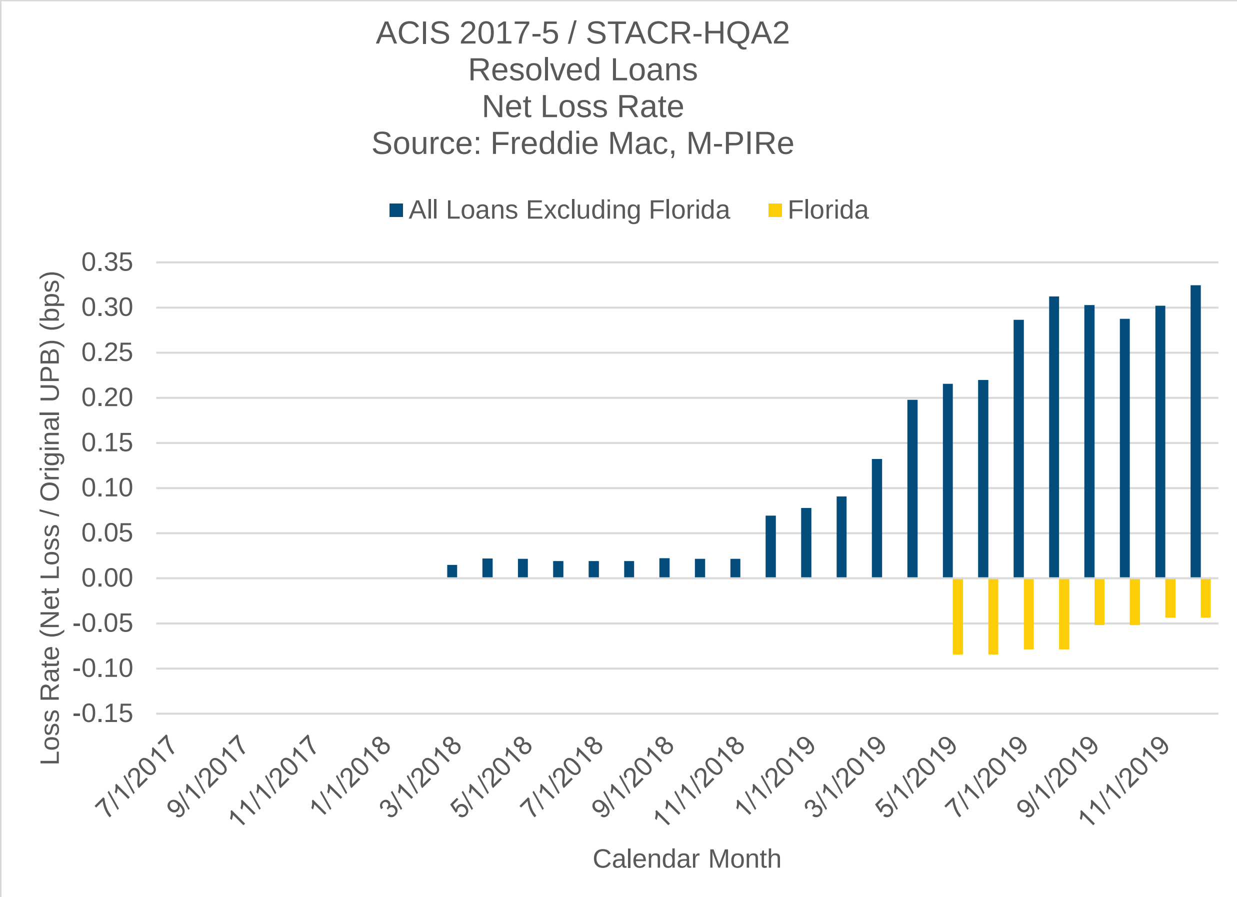


Figure 24 provides similar information for the ACIS 2017-5 / STACR 2017-HQA2 transaction. For this transaction, cumulative losses in Florida are actually negative, indicating the amount recovered from foreclosures plus mortgage guaranty insurance has exceeded the defaulting principal balance plus expenses and delinquent interest.

These results are not consistent with the model assumptions in the prior section, which expected an increase in actual losses following a natural disaster. This type of performance is not unique to Hurricane Irma, and similar results have been observed following other events. Specifically, the data indicates that while natural disasters may result in a spike in delinquencies, the majority of impacted loans either cure or prepay following the event. Few mortgages result in a realized loss to the investor. It is difficult to pinpoint the reason for this observation, but potential contributors are:

1. Some borrowers did have flood insurance during these events.

2. The disaster assistance offered by mortgage investors provided effective relief to borrowers.

3. Some uninsured borrowers received state or federal assistance to repair their homes.

4. Some borrowers may have been uninsured for flood losses but insured for wind losses and may have received payment from their insurance company for some of their flood losses even though such protection was not provided under their policies.

5. Some historical natural disasters occurred during periods of relative strength in the housing market. That is, for the sparse record of observable extreme events, most did not occur while home prices were declining and the borrowers were "underwater" on their mortgages. Thus, relying on the historical record may understate the true

potential risk associated with this issue if a disaster were to occur under stressed economic conditions, or if future disaster assistance programs did not provide the same relief as past ones.

6. Homeowners and communities may have a stronger desire to rebuild following a natural disasters than during other circumstances that could affect their mortgages.

The disconnect between model estimates resulting from the methodology presented in this paper and historical performance indicates that more study is still needed on this issue. Nevertheless, the estimates and methodology can provide a useful benchmark in determining a priori expectations for mortgage investors to which historical performance can be compared. Based on our examination of Hurricane Irma, it appears that the threat of natural catastrophes to mortgage credit risk may be smaller than this a priori expectation would indicate, possibly due to the fact that assistance or forgiveness programs have acted as mitigating factors to prevent a realization of the potential downside associated with uninsured homeowners defaulting on their mortgages.

Note that these empirically observed outcomes are only particular to one disaster. Different disasters and different impacted regions may have materially different outcomes that what was observed after Hurricane Irma. For instance, the relatively benign to-date outcomes of the impacted loans may be partially driven by Florida's longer-than-average foreclosure timelines. Reviewing similar data post-Hurricane-Harvey shows moderately higher losses in the region (as compared to similar data post-Irma). Texas has a quicker foreclosure process, and delinquencies may translate into losses more quickly than in Florida, all else equal. Nevertheless, our review finds that actual losses from recent natural catastrophes are relatively small as compared to the model estimates and methodology presented in the above sections. This is consistent with the finding from Irma: The threat of natural catastrophes to mortgages credit risk may be smaller than this a priori expectation would indicate.

However, if the frequency of natural disasters increases with climate change, then it would also become increasingly costly for taxpayers and GSEs to continue to provide these types of assistance to affected borrowers, and if the same degree of assistance were not to continue, then the performance of mortgages following these events could be worse.

Furthermore, borrowers in areas impacted by climate change may be less resilient in the future. They may decide not to rebuild because of the threat that their properties could continue to be impacted by similar events, so the transition from delinquency to foreclosure and loss could rise in the future.

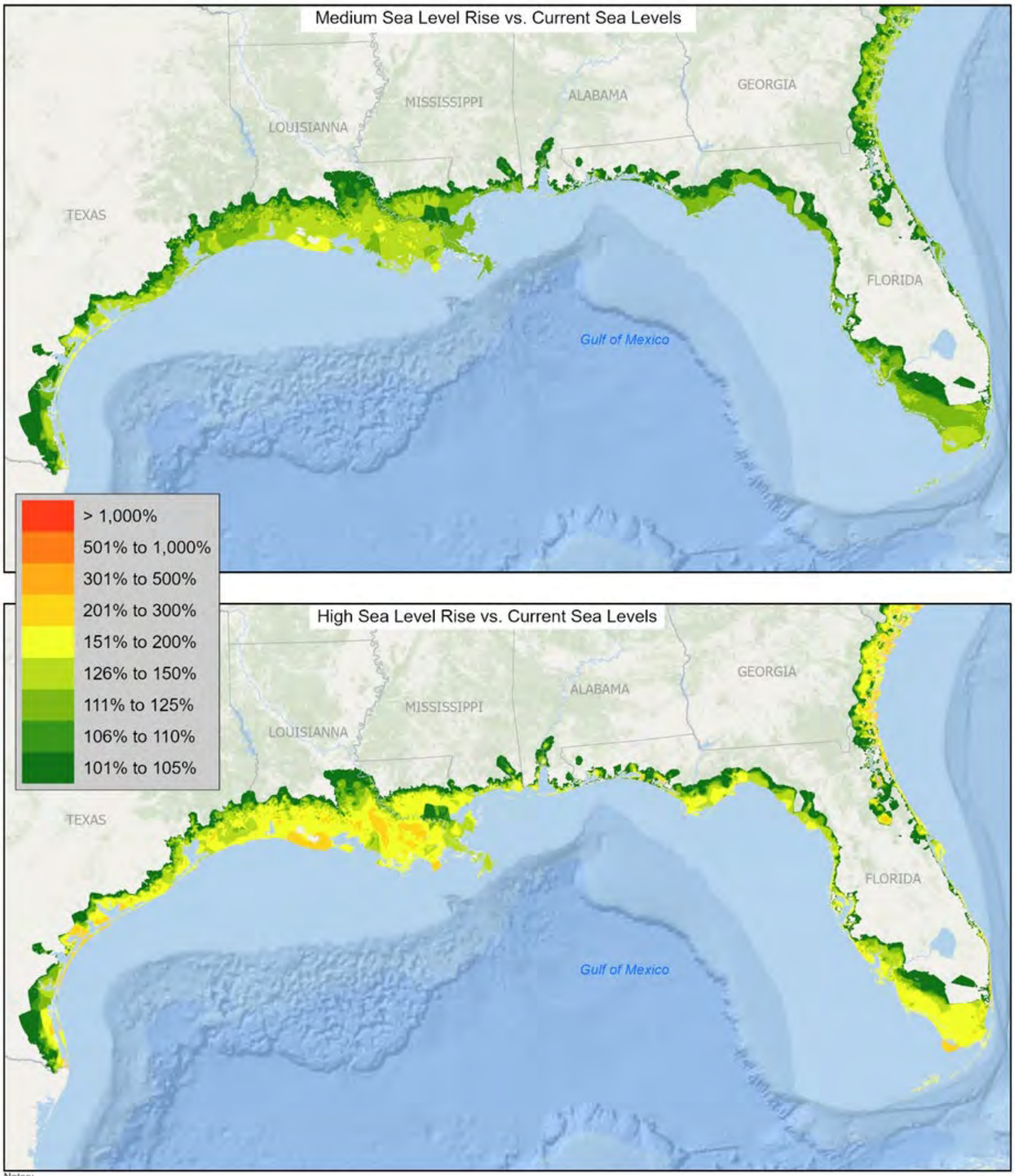
Because of limitations in the historical data available to analyze mortgage performance during disasters across different credit cycles, it could be possible that natural catastrophes may pose more mortgage credit downside relative to recent experience. But the historical record simply lacks any "perfect storm" observations that contain the combination of event severity and economic circumstances that could give rise to significant impairment in mortgage investments, despite the possibility that such an event could occur. Thus, any effort to quantify the potential effects of this issue should recognize the limitations of the historical record and employ a methodology that recognizes the full range of possible events that could occur.

5. Appendix

5.1 MAPS: INCREASE IN EXPECTED FLOOD LOSSES UNDER SEA LEVEL RISE SCENARIOS

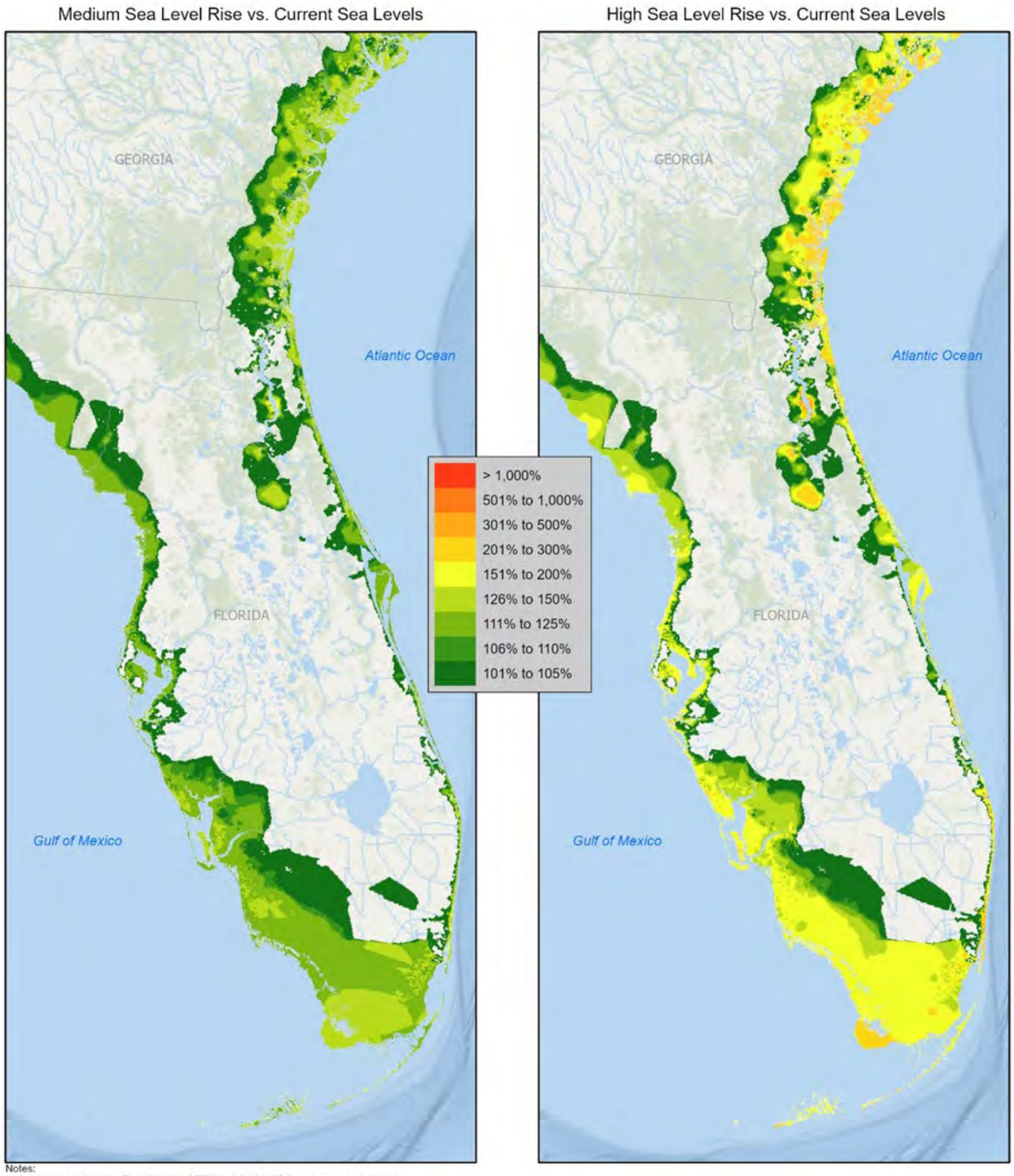
Each map in this report shows the increase in total flood losses under sea level rise scenarios. Results are spatially smoothed using inverse distance weighting (IDW) interpolation performed on the modeled market basket locations. The ratios of total flood losses for the market basket locations were calculated between different sea level rise scenarios and were run through ESRI's IDW tool. IDW converts an input dataset of points into a continuous one-kilometer grid layer by calculating a weighted average of the 10 closest data points at each cell location. The tool is able to smooth the values of cells at locations that lack sampled points by assuming that the variable being mapped decreases in influence with distance and by weighting the surrounding values based on their inverse distances from that location.

Map 1: Ratios of Expected Flood Losses; Sea Level Rise Scenarios to Current Sea Level - Gulf of Mexico



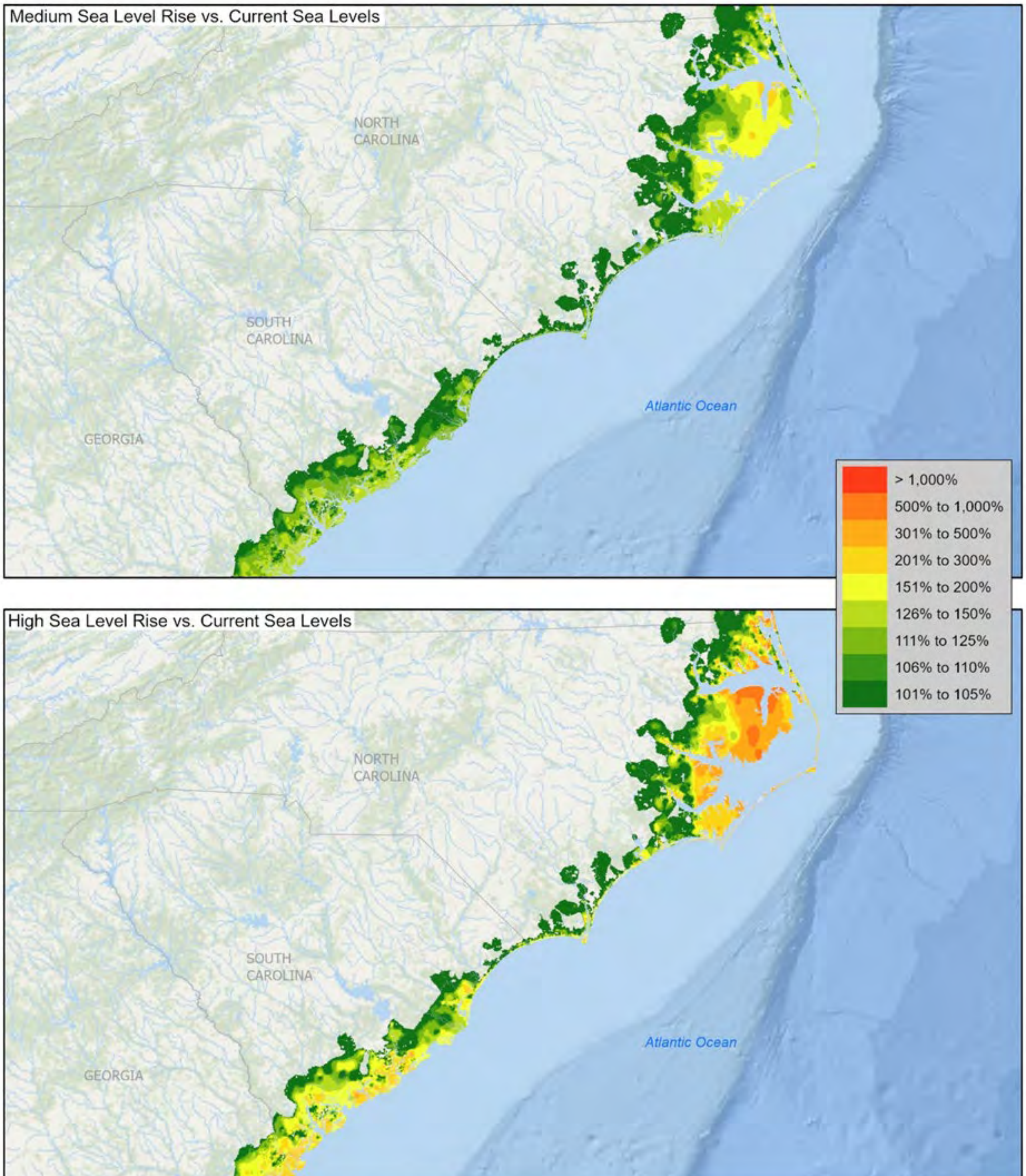
Notes:
1. Service Layer Credits: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors

Map 2: Expected Flood Losses; Sea Level Rise Scenarios to Current Sea Level - Florida to Georgia



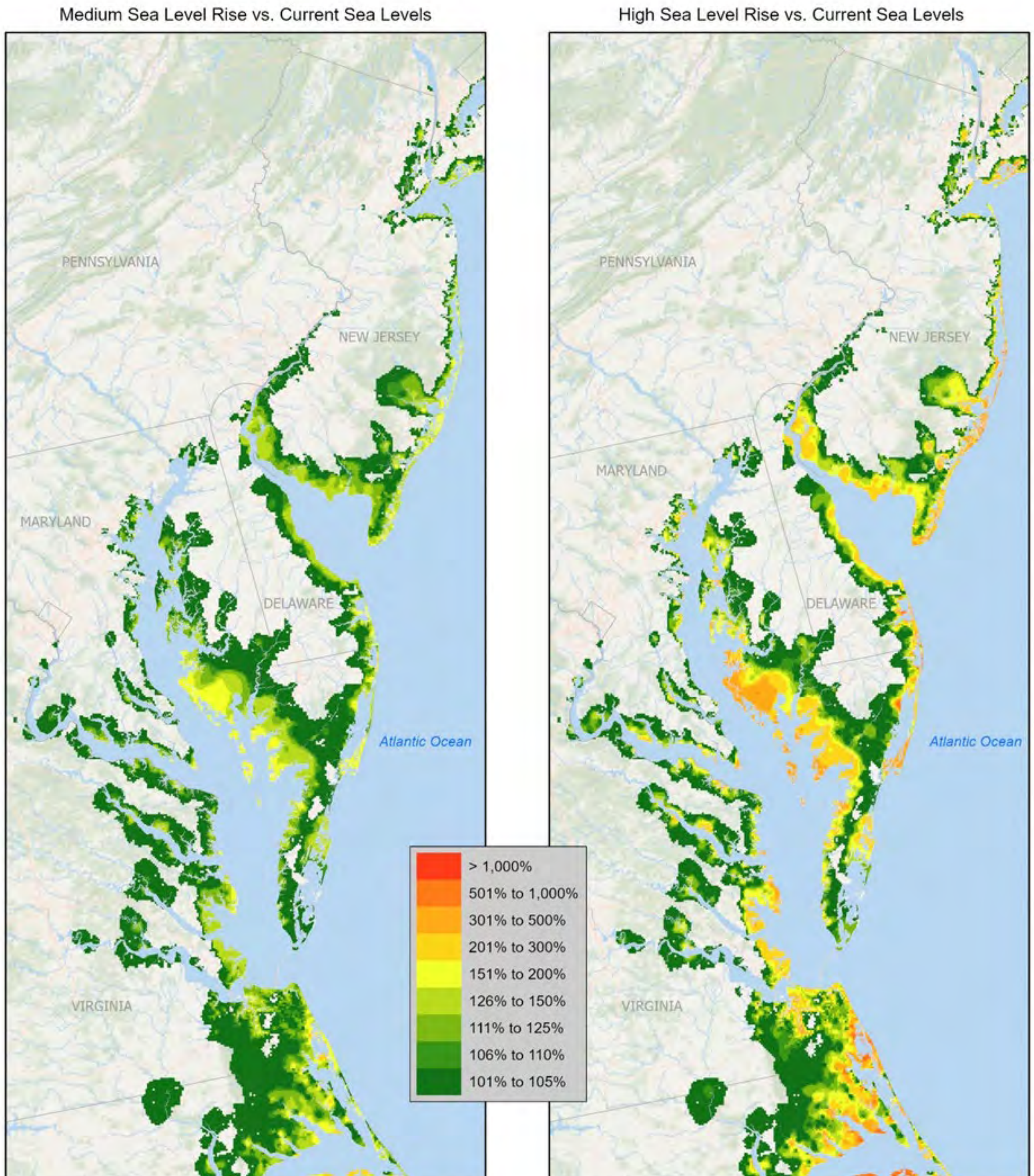
Notes:
1. Service Layer Credits: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors

Map 3: Expected Flood Losses; Sea Level Rise Scenarios to Current Sea Level – Carolinas



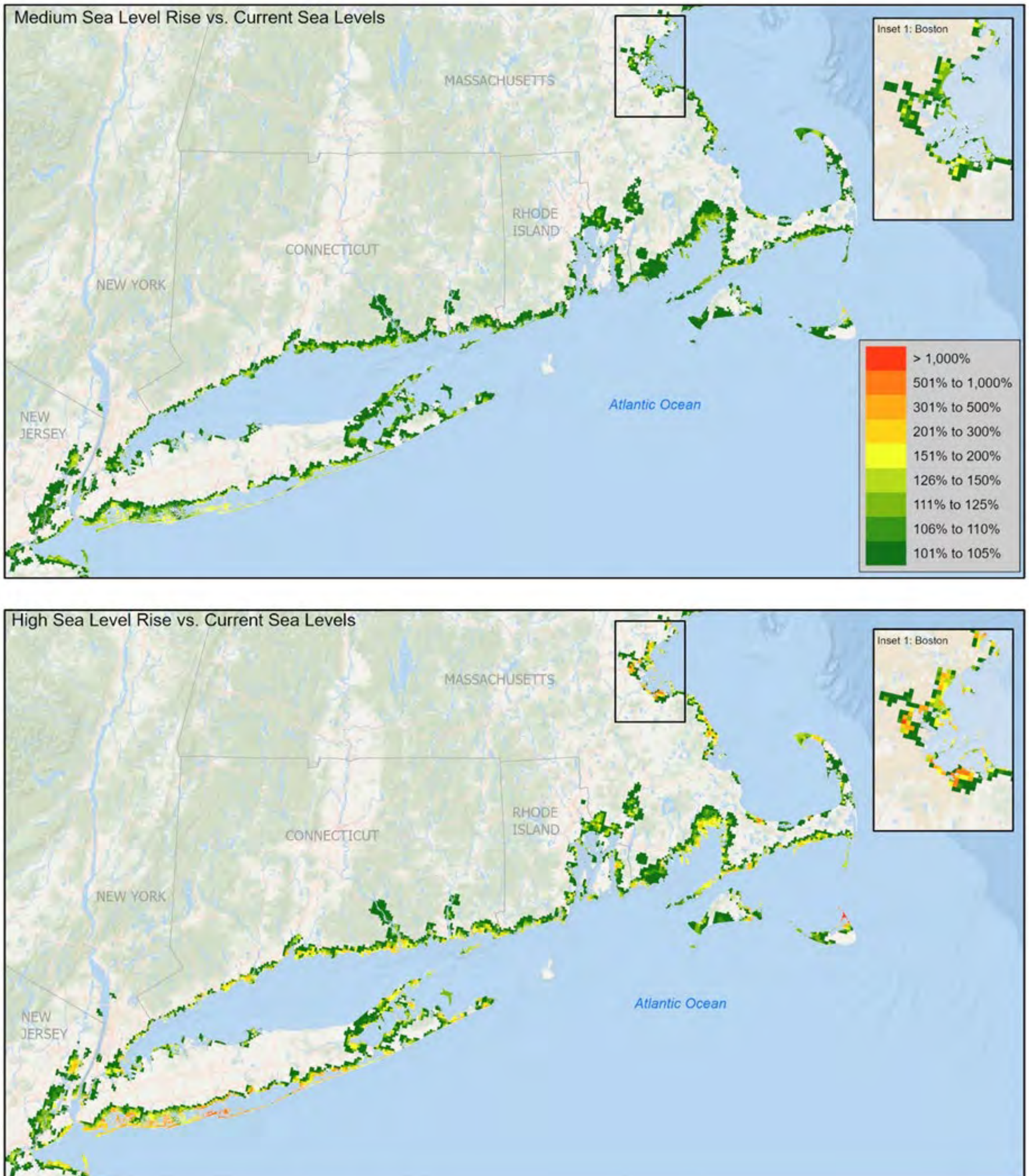
Notes:
1. Service Layer Credits: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors

Map 4: Expected Flood Losses; Sea Level Rise Scenarios to Current Sea Level – Mid-Atlantic



Notes:
1. Service Layer Credits: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors

Map 5: Expected Flood Losses; Sea Level Rise Scenarios to Current Sea Level – Northeast



Notes:
1. Service Layer Credits: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors

5.2 EXHIBITS

Exhibit 7: Development of NFIP Take-Up Rate Assumptions

(1)	(2)	(3)	(4)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Estimated Single Family Home NFIP Take-up			NFIP Policy Count			Number of Single Family Homes			Single Family Homes not Insured by NFIP		
State	Total	SFHA	Non SFHA	Total	SFHA	Non SFHA	Total	SFHA	Non SFHA	Total	SFHA	Non SFHA
Alabama	1.7%	23.5%	0.9%	32,517	16,735	15,782	1,863,170	71,137	1,792,033	1,830,653	54,402	1,776,251
Arizona	1.1%	28.0%	0.5%	25,304	14,520	10,784	2,332,748	51,781	2,280,967	2,307,444	37,261	2,270,183
Arkansas	1.1%	14.0%	0.4%	12,344	7,545	4,799	1,133,948	53,777	1,080,171	1,121,604	46,232	1,075,372
California	1.9%	31.6%	1.1%	185,387	85,848	99,539	9,628,644	272,066	9,356,578	9,443,257	186,218	9,257,039
Colorado	0.8%	19.3%	0.6%	13,753	4,377	9,376	1,720,260	22,702	1,697,558	1,706,507	18,325	1,688,182
Connecticut	2.4%	29.7%	1.1%	23,599	13,243	10,356	985,578	44,629	940,949	961,979	31,386	930,593
Delaware	5.0%	41.0%	2.2%	17,257	10,106	7,151	348,602	24,626	323,976	331,345	14,520	316,825
Florida	15.5%	51.3%	9.0%	999,832	507,579	492,253	6,437,823	989,468	5,448,355	5,437,991	481,889	4,956,102
Georgia	2.2%	24.2%	1.4%	74,149	30,042	44,107	3,335,899	124,220	3,211,679	3,261,750	94,178	3,167,572
Idaho	0.8%	12.4%	0.4%	4,667	2,263	2,404	594,681	18,320	576,361	590,014	16,057	573,957
Illinois	0.8%	22.7%	0.4%	29,013	16,626	12,387	3,580,795	73,396	3,507,399	3,551,782	56,770	3,495,012
Indiana	0.8%	14.7%	0.4%	18,492	9,908	8,584	2,322,891	67,300	2,255,591	2,304,399	57,392	2,247,007
Iowa	0.8%	13.7%	0.4%	8,705	4,342	4,363	1,115,953	31,717	1,084,236	1,107,248	27,375	1,079,873
Kansas	0.7%	10.3%	0.4%	7,467	3,094	4,373	1,030,486	30,160	1,000,326	1,023,019	27,066	995,953
Kentucky	1.0%	15.0%	0.4%	16,087	10,372	5,715	1,604,688	69,224	1,535,464	1,588,601	58,852	1,529,749
Louisiana	25.8%	51.5%	19.8%	424,592	160,350	264,242	1,647,501	311,322	1,336,179	1,222,909	150,972	1,071,937
Maine	1.0%	11.7%	0.6%	6,076	2,586	3,490	596,095	22,110	573,985	590,019	19,524	570,495
Maryland	2.0%	45.3%	1.2%	35,239	14,392	20,847	1,806,078	31,761	1,774,317	1,770,839	17,369	1,753,470
Massachusetts	2.2%	24.6%	1.2%	36,375	17,075	19,300	1,671,803	69,436	1,602,367	1,635,428	52,361	1,583,067
Michigan	0.4%	12.3%	0.2%	16,850	10,606	6,244	3,756,861	86,119	3,670,742	3,740,011	75,513	3,664,498
Minnesota	0.4%	8.5%	0.2%	7,254	2,692	4,562	1,875,707	31,847	1,843,860	1,868,453	29,155	1,839,298
Mississippi	4.7%	21.1%	3.1%	52,221	20,150	32,071	1,117,509	95,311	1,022,198	1,065,288	75,161	990,127
Missouri	0.7%	16.7%	0.3%	14,586	8,233	6,353	2,208,296	49,306	2,158,990	2,193,710	41,073	2,152,637
Montana	1.1%	9.9%	0.8%	4,519	1,418	3,101	419,516	14,365	405,151	414,997	12,947	402,050
Nebraska	1.0%	16.8%	0.4%	6,763	4,468	2,295	659,090	26,518	632,572	652,327	22,050	630,277
Nevada	1.1%	32.1%	0.5%	9,745	5,587	4,158	850,493	17,423	833,070	840,748	11,836	828,912
New Hampshire	1.0%	15.3%	0.5%	4,616	2,505	2,111	468,372	16,356	452,016	463,756	13,851	449,905
New Jersey	5.4%	48.2%	1.4%	123,495	93,404	30,091	2,303,561	193,976	2,109,585	2,180,066	100,572	2,079,494
New Mexico	1.4%	13.8%	0.5%	10,832	6,889	3,943	787,714	49,745	737,969	776,882	42,856	734,026
New York	3.0%	37.9%	1.8%	123,657	54,793	68,864	4,074,892	144,683	3,930,209	3,951,235	89,890	3,861,345
North Carolina	2.9%	40.5%	1.2%	107,484	62,893	44,591	3,727,599	155,106	3,572,493	3,620,115	92,213	3,527,902
North Dakota	3.2%	10.8%	2.7%	8,344	1,870	6,474	256,899	17,381	239,518	248,555	15,511	233,044
Ohio	0.6%	16.3%	0.3%	24,911	13,602	11,309	3,980,674	83,460	3,897,214	3,955,763	69,858	3,885,905
Oklahoma	0.8%	11.2%	0.4%	10,833	4,931	5,902	1,441,948	43,988	1,397,960	1,431,115	39,057	1,392,058
Oregon	1.6%	23.4%	0.8%	20,780	10,516	10,264	1,320,983	44,951	1,276,032	1,300,203	34,435	1,265,768
Pennsylvania	0.9%	16.1%	0.5%	40,193	18,656	21,537	4,506,700	116,128	4,390,572	4,466,507	97,472	4,369,035
Rhode Island	3.4%	43.2%	1.8%	9,370	4,491	4,879	276,748	10,384	266,364	267,378	5,893	261,485
South Carolina	7.8%	(Note 7)	3.4%	142,467	83,533	58,934	1,834,704	102,795	1,731,909	1,692,237	(Note 7)	0
South Dakota	0.9%	10.9%	0.5%	2,752	1,203	1,549	308,314	11,040	297,274	305,562	9,837	295,725
Tennessee	0.9%	19.3%	0.5%	21,994	9,476	12,518	2,352,974	49,165	2,303,809	2,330,980	39,689	2,291,291
Texas	8.4%	33.7%	7.1%	669,789	133,754	536,035	7,978,382	397,440	7,580,942	7,308,593	263,686	7,044,907
Utah	0.3%	7.3%	0.3%	2,708	590	2,118	820,270	8,067	812,203	817,562	7,477	810,085
Vermont	0.9%	16.8%	0.5%	2,335	1,177	1,158	256,291	7,012	249,279	253,956	5,835	248,121
Virginia	3.1%	41.6%	1.8%	84,188	35,793	48,395	2,703,730	85,942	2,617,788	2,619,542	50,149	2,569,393
Washington	1.3%	32.2%	0.6%	28,092	15,321	12,771	2,233,400	47,631	2,185,769	2,205,308	32,310	2,172,998
West Virginia	1.6%	13.5%	0.6%	12,513	8,301	4,212	781,324	61,348	719,976	768,811	53,047	715,764
Wisconsin	0.5%	10.4%	0.2%	9,780	4,985	4,795	1,985,427	47,783	1,937,644	1,975,647	42,798	1,932,849
Wyoming	0.6%	10.5%	0.4%	1,485	564	921	230,105	5,371	224,734	228,620	4,807	223,813
Total (Note 6)	3.6%	34.2%	2.1%	3,545,411	1,553,404	1,992,007	99,276,126	4,399,795	94,876,331	95,730,715	2,894,761	92,907,315

Notes:

1. Take-up in Columns (2) through (4) is the ratio of NFIP single family dwelling policies to single family homes. Policies and homes were counted in total, inside the Special Flood Hazard Area (SFHA), and outside the SFHA.
2. NFIP single family dwelling policies, in force as of September 30, 2018, were determined using the June 2019 release of OpenFEMA NFIP policy data. These include policies for mobile homes. Policies were counted in total, inside the SFHA, and outside of the SFHA.
3. Total single family homes were determined using the 2017 American Community Survey 5 year estimate. Single family attached, single family detached, and mobile home counts were included.
4. Single family homes inside and outside the SFHA were calculated by allocating the total home counts with distributions based on Market Baskets.
5. Each Market Basket represents a sample of actual locations of real risks in the marketplace. Market Baskets contain approximately 10% of the single family home locations in each state.
6. Total row does not include Alaska, District of Columbia, Hawaii, or Territories of the United States.
7. Take-up rate estimates inside and outside SFHA for South Carolina are currently unavailable.

Exhibit 8: Modeled Insured and Uninsured Losses by MSA

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Metropolitan	Single Family	Average Annual Losses			Annual Losses			Percent of
Statistical Area Title	Residences	Insured	Uninsured	Total	Insured	Uninsured	Total	Losses Uninsured
(Note 1)	(Note 1)	(Note 2)	(Note 2)	(Note 2)	= (2) * (3)	= (2) * (4)	= (5) + (6)	= (6) / (7)
Hilton Head Island-Bluffton, SC	72,147	$225	$1,763	$1,988	$16,251,239	$127,206,009	$143,457,248	88.7%
Houma-Thibodaux, LA	60,417	256	669	925	15,450,541	40,425,486	55,876,027	72.3%
Naples-Marco Island, FL	95,685	357	654	1,011	34,175,531	62,606,094	96,781,625	64.7%
Punta Gorda, FL	70,708	350	614	963	24,735,052	43,380,277	68,115,329	63.7%
Napa, CA	41,795	9	538	547	377,749	22,485,975	22,863,724	98.3%
Cape Coral-Fort Myers, FL	238,495	269	534	803	64,053,011	127,404,015	191,457,026	66.5%
New Orleans-Metairie, LA	371,993	177	516	694	65,886,138	192,129,455	258,015,593	74.5%
Sebastian-Vero Beach, FL	52,438	35	470	505	1,841,690	24,637,086	26,478,775	93.0%
Ocean City, NJ	75,589	166	440	606	12,511,248	33,295,161	45,806,409	72.7%
Wenatchee, WA	37,375	6	329	335	209,661	12,303,994	12,513,655	98.3%
Beaumont-Port Arthur, TX	120,529	32	321	353	3,884,590	38,707,512	42,592,102	90.9%
Jacksonville, NC	53,490	138	318	456	7,378,136	16,986,873	24,365,009	69.7%
Santa Cruz-Watsonville, CA	76,110	7	295	303	569,633	22,477,038	23,046,671	97.5%
Santa Rosa-Petaluma, CA	159,048	14	242	256	2,262,874	38,457,232	40,720,106	94.4%
St. George, UT	52,060	0	225	225	0	11,735,854	11,735,854	100.0%
Lake Charles, LA	62,822	104	219	323	6,522,451	13,750,763	20,273,215	67.8%
Wilmington, NC	93,347	40	209	248	3,711,650	19,482,542	23,194,192	84.0%
Bend, OR	65,818	1	199	200	46,605	13,108,708	13,155,313	99.6%
Charleston-North Charleston, SC	212,033	95	198	293	20,196,030	41,884,724	62,080,754	67.5%
San Jose-Sunnyvale-Santa Clara, CA	433,002	13	196	209	5,505,301	85,069,419	90,574,720	93.9%
Santa Maria-Santa Barbara, CA	101,415	5	191	197	552,315	19,402,243	19,954,557	97.2%
Oxnard-Thousand Oaks-Ventura, CA	214,030	16	180	196	3,434,263	38,537,513	41,971,776	91.8%
Miami-Fort Lauderdale-Pompano Beach, FL	1,292,465	52	177	229	66,996,364	229,248,792	296,245,156	77.4%
Grants Pass, OR	27,766	18	176	194	496,217	4,898,611	5,394,828	90.8%
Hot Springs, AR	34,799	0	176	176	5,908	6,130,445	6,136,353	99.9%
Brunswick, GA	37,880	26	176	202	986,323	6,671,067	7,657,390	87.1%
Daphne-Fairhope-Foley, AL	70,318	22	168	190	1,544,017	11,805,790	13,349,807	88.4%
Homosassa Springs, FL	55,727	78	167	245	4,329,909	9,325,620	13,655,529	68.3%
Los Angeles-Long Beach-Anaheim, CA	2,637,020	2	166	169	5,450,959	438,945,936	444,396,895	98.8%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	156,898	62	165	227	9,680,192	25,881,580	35,561,772	72.8%
Charleston, WV	91,961	11	164	175	976,720	15,075,368	16,052,087	93.9%
North Port-Sarasota-Bradenton, FL	263,971	76	163	239	20,142,829	42,996,783	63,139,612	68.1%
Lake Havasu City-Kingman, AZ	69,892	20	163	182	1,375,208	11,361,314	12,736,521	89.2%
Yuba City, CA	46,641	3	161	164	136,787	7,490,238	7,627,026	98.2%
Flagstaff, AZ	43,823	9	146	155	373,357	6,416,249	6,789,606	94.5%
Bridgeport-Stamford-Norwalk, CT	238,970	23	142	165	5,463,805	33,870,132	39,333,937	86.1%
San Francisco-Oakland-Berkeley, CA	1,053,639	5	130	136	5,544,929	137,406,918	142,951,847	96.1%
Riverside-San Bernardino-Ontario, CA	1,142,048	4	129	133	4,244,809	147,637,490	151,882,300	97.2%
Eugene-Springfield, OR	108,311	9	129	137	931,339	13,933,106	14,864,445	93.7%
Jacksonville, FL	429,019	31	128	159	13,090,295	54,957,280	68,047,575	80.8%
Palm Bay-Melbourne-Titusville, FL	190,403	14	128	142	2,725,675	24,382,064	27,107,739	89.9%
Austin-Round Rock-Georgetown, TX	496,025	13	124	137	6,538,712	61,379,423	67,918,136	90.4%
Port St. Lucie, FL	147,959	33	120	154	4,935,659	17,806,741	22,742,400	78.3%
Portland-South Portland, ME	193,001	8	120	128	1,559,702	23,093,226	24,652,928	93.7%
Bowling Green, KY	49,659	3	117	120	144,621	5,825,760	5,970,381	97.6%
Houston-The Woodlands-Sugar Land, TX	1,649,856	12	117	129	19,638,279	192,737,803	212,376,082	90.8%
Lafayette, LA	141,177	73	116	189	10,257,000	16,435,980	26,692,981	61.6%
Madera, CA	40,942	6	111	116	231,268	4,537,215	4,768,484	95.2%
Gulfport-Biloxi, MS	130,147	21	109	130	2,750,538	14,209,538	16,960,076	83.8%
Longview, WA	30,847	0	109	109	421	3,367,033	3,367,454	100.0%
Tampa-St. Petersburg-Clearwater, FL	849,853	53	108	161	45,283,390	91,553,938	136,837,328	66.9%
Pittsfield, MA	46,831	11	107	118	517,556	5,011,584	5,529,140	90.6%
Reno, NV	125,517	8	105	113	951,172	13,185,536	14,136,708	93.3%
Deltona-Daytona Beach-Ormond Beach, FL	220,757	31	105	135	6,747,605	23,154,651	29,902,256	77.4%
Sioux City, IA-NE-SD	45,531	1	105	106	49,585	4,771,404	4,820,989	99.0%
Beckley, WV	44,391	7	104	111	296,101	4,638,646	4,934,747	94.0%
New Haven-Milford, CT	213,870	15	103	119	3,264,959	22,099,225	25,364,184	87.1%
New York-Newark-Jersey City, NY-NJ-PA	3,262,366	17	102	120	57,037,811	332,933,472	389,971,283	85.4%
San Luis Obispo-Paso Robles, CA	87,318	4	98	101	308,638	8,517,183	8,825,820	96.5%
Barnstable Town, MA	138,885	6	96	102	846,437	13,271,242	14,117,678	94.0%
Prescott Valley-Prescott, AZ	77,916	2	95	97	165,379	7,394,507	7,559,886	97.8%
Albany-Lebanon, OR	35,729	2	94	96	87,088	3,342,659	3,429,747	97.5%
Williamsport, PA	39,686	3	93	96	129,168	3,681,444	3,810,613	96.6%
San Antonio-New Braunfels, TX	608,824	11	92	103	6,823,906	56,180,166	63,004,073	89.2%
Salinas, CA	97,116	12	92	104	1,156,612	8,941,956	10,098,568	88.5%
Cumberland, MD-WV	35,918	4	90	94	127,897	3,238,922	3,366,819	96.2%
Mobile, AL	139,996	12	90	102	1,653,555	12,613,633	14,267,187	88.4%
Tucson, AZ	306,712	3	88	91	1,072,406	26,935,244	28,007,650	96.2%
Savannah, GA	109,497	14	87	101	1,538,723	9,543,127	11,081,849	86.1%
Billings, MT	56,865	2	86	87	85,618	4,863,330	4,948,948	98.3%
Medford, OR	64,532	0	85	86	17,400	5,506,433	5,523,832	99.7%
Chambersburg-Waynesboro, PA	49,867	0	84	84	4,884	4,172,498	4,177,382	99.9%
New Bern, NC	41,778	23	83	106	971,149	3,472,857	4,444,006	78.1%
Virginia Beach-Norfolk-Newport News, VA-NC	523,327	23	83	106	12,096,352	43,311,633	55,407,985	78.2%
Mount Vernon-Anacortes, WA	40,761	4	83	86	148,860	3,368,352	3,517,213	95.8%

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Metropolitan Statistical Area Title (Note 1)	Single Family Residences (Note 1)	Average Annual Losses			Annual Losses			Percent of Losses Uninsured
		Insured (Note 2)	Uninsured (Note 2)	Total (Note 2)	Insured = (2) * (3)	Uninsured = (2) * (4)	Total = (5) + (6)	= (6) / (7)
Staunton, VA	41,608	13	82	96	552,832	3,426,402	3,979,233	86.1%
Alexandria, LA	46,253	13	81	94	591,478	3,767,970	4,359,448	86.4%
Wheeling, WV-OH	52,569	20	80	100	1,066,591	4,190,213	5,256,804	79.7%
Altoona, PA	43,171	5	78	83	213,844	3,373,587	3,587,431	94.0%
Huntington-Ashland, WV-KY-OH	119,667	6	77	83	679,947	9,249,409	9,929,357	93.2%
Great Falls, MT	27,286	0	76	77	12,751	2,085,497	2,098,248	99.4%
Ithaca, NY	23,291	9	76	85	213,438	1,773,870	1,987,308	89.3%
Boston-Cambridge-Newton, MA-NH	1,042,909	9	75	84	8,880,563	78,344,793	87,225,356	89.8%
Nashville-Davidson--Murfreesboro--Franklin, TN	519,278	7	74	82	3,741,000	38,601,214	42,342,214	91.2%
Crestview-Fort Walton Beach-Destin, FL	92,891	19	74	93	1,788,168	6,827,948	8,616,116	79.2%
Lawton, OK	40,987	4	73	77	151,071	2,990,248	3,141,319	95.2%
Scranton--Wilkes-Barre, PA	196,581	2	73	75	425,798	14,268,821	14,694,619	97.1%
State College, PA	43,484	6	72	78	247,829	3,145,218	3,393,047	92.7%
Santa Fe, NM	51,421	0	72	72	8,269	3,710,411	3,718,681	99.8%
Rapid City, SD	40,492	1	70	72	56,559	2,848,110	2,904,669	98.1%
Kingston, NY	61,429	20	70	90	1,224,570	4,307,204	5,531,774	77.9%
Weirton-Steubenville, WV-OH	46,020	1	69	70	57,552	3,161,733	3,219,285	98.2%
Norwich-New London, CT	85,235	14	67	81	1,199,595	5,691,199	6,890,794	82.6%
Gainesville, FL	75,798	16	67	82	1,201,971	5,043,305	6,245,276	80.8%
Vallejo, CA	117,267	1	66	67	102,258	7,781,757	7,884,015	98.7%
Lexington-Fayette, KY	151,953	3	66	68	411,672	9,970,271	10,381,942	96.0%
Corvallis, OR	24,463	9	66	74	211,527	1,603,815	1,815,342	88.3%
Johnson City, TN	65,574	7	65	72	434,537	4,291,081	4,725,619	90.8%
Midland, MI	28,572	0	65	65	1,015	1,855,539	1,856,554	99.9%
College Station-Bryan, TX	58,227	7	64	72	428,291	3,741,415	4,169,706	89.7%
Redding, CA	56,712	3	63	66	182,040	3,582,454	3,764,494	95.2%
Phoenix-Mesa-Chandler, AZ	1,315,715	1	62	63	772,156	82,057,951	82,830,106	99.1%
Poughkeepsie-Newburgh-Middletown, NY	180,872	6	62	67	1,023,722	11,163,676	12,187,397	91.6%
Rochester, MN	70,522	0	61	61	26,637	4,288,454	4,315,090	99.4%
Cape Girardeau, MO-IL	31,409	4	61	65	139,792	1,904,248	2,044,040	93.2%
Salisbury, MD-DE	161,632	40	59	99	6,397,430	9,576,224	15,973,654	60.0%
Midland, TX	41,584	7	59	66	285,110	2,458,535	2,743,645	89.6%
Missoula, MT	34,018	2	59	61	65,298	2,005,936	2,071,234	96.8%
Las Vegas-Henderson-Paradise, NV	559,062	0	59	59	192,703	32,907,794	33,100,497	99.4%
Bakersfield, CA	216,228	2	58	59	326,213	12,508,438	12,834,651	97.5%
St. Louis, MO-IL	921,436	1	58	59	1,007,975	53,094,179	54,102,154	98.1%
Elizabethtown-Fort Knox, KY	45,116	2	57	59	74,848	2,593,802	2,668,649	97.2%
Grand Forks, ND-MN	27,893	1	56	58	40,218	1,575,550	1,615,768	97.5%
Stockton, CA	186,972	1	56	57	183,342	10,529,540	10,712,882	98.3%
Lafayette-West Lafayette, IN	63,208	6	56	63	405,573	3,555,096	3,960,668	89.8%
San Diego-Chula Vista-Carlsbad, CA	726,052	2	56	58	1,750,789	40,529,427	42,280,216	95.9%
Little Rock-North Little Rock-Conway, AR	221,251	1	56	57	181,874	12,324,913	12,506,787	98.5%
Boise City, ID	209,649	1	55	56	268,068	11,435,350	11,703,417	97.7%
Harrisonburg, VA	38,963	2	54	57	87,123	2,114,994	2,202,117	96.0%
Corpus Christi, TX	121,799	6	54	60	707,546	6,547,910	7,255,456	90.2%
Baton Rouge, LA	241,791	29	53	82	7,041,292	12,868,309	19,909,601	64.6%
Grand Island, NE	24,206	1	53	54	16,903	1,286,594	1,303,497	98.7%
Manchester-Nashua, NH	107,925	3	53	56	345,673	5,673,837	6,019,510	94.3%
Brownsville-Harlingen, TX	98,581	6	52	59	613,763	5,153,909	5,767,671	89.4%
Las Cruces, NM	53,007	3	52	55	132,962	2,771,238	2,904,200	95.4%
Louisville/Jefferson County, KY-IN	392,146	1	52	53	360,506	20,462,652	20,823,159	98.3%
Bloomsburg-Berwick, PA	28,762	2	52	54	44,278	1,498,284	1,542,562	97.1%
Panama City, FL	55,465	13	52	65	726,921	2,865,778	3,592,699	79.8%
Pensacola-Ferry Pass-Brent, FL	151,893	16	51	67	2,376,051	7,809,647	10,185,699	76.7%
Boulder, CO	89,651	0	51	51	9,018	4,588,452	4,597,470	99.8%
Chattanooga, TN-GA	176,731	9	51	60	1,564,998	8,954,892	10,519,890	85.1%
Visalia, CA	114,421	1	50	51	166,221	5,714,612	5,880,832	97.2%
McAllen-Edinburg-Mission, TX	181,583	6	50	56	1,049,737	9,051,988	10,101,724	89.6%
Fayetteville-Springdale-Rogers, AR	145,087	1	50	51	119,383	7,223,858	7,343,241	98.4%
Muskegon, MI	59,101	0	49	50	19,181	2,918,661	2,937,843	99.3%
Fargo, ND-MN	58,483	1	48	49	70,152	2,799,839	2,869,990	97.6%
Hammond, LA	34,396	30	48	77	1,017,770	1,637,528	2,655,297	61.7%
Greenville, NC	44,156	4	47	51	160,634	2,084,098	2,244,732	92.8%
Springfield, MA	180,427	1	47	48	228,406	8,515,132	8,743,537	97.4%
Ocala, FL	114,452	6	47	53	686,275	5,382,872	6,069,148	88.7%
Portland-Vancouver-Hillsboro, OR-WA	649,684	3	47	50	2,195,299	30,440,786	32,636,085	93.3%
Merced, CA	65,808	2	46	49	154,724	3,056,402	3,211,125	95.2%
Bismarck, ND	36,364	1	46	47	32,496	1,671,430	1,703,926	98.1%
Yakima, WA	61,726	3	46	49	160,434	2,834,510	2,994,944	94.6%
Asheville, NC	152,118	7	46	53	1,122,995	6,967,070	8,090,065	86.1%
Sebring-Avon Park, FL	34,415	5	46	51	172,408	1,574,321	1,746,729	90.1%
Trenton-Princeton, NJ	103,091	12	45	57	1,216,111	4,655,716	5,871,826	79.3%
Michigan City-La Porte, IN	38,341	4	45	49	135,222	1,725,323	1,860,545	92.7%
Fort Collins, CO	105,570	0	45	45	45,756	4,735,253	4,781,009	99.0%
Oklahoma City, OK	419,811	1	45	46	379,423	18,828,484	19,207,907	98.0%

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Metropolitan	Single Family	Average Annual Losses			Annual Losses			Percent of
Statistical Area Title	Residences	Insured	Uninsured	Total	Insured	Uninsured	Total	Losses Uninsured
(Note 1)	(Note 1)	(Note 2)	(Note 2)	(Note 2)	= (2) * (3)	= (2) * (4)	= (5) + (6)	= (6) / (7)
Allentown-Bethlehem-Easton, PA-NJ	268,248	7	45	51	1,806,954	11,968,097	13,775,051	86.9%
Hartford-East Hartford-Middletown, CT	332,941	6	44	50	1,964,887	14,810,069	16,774,956	88.3%
Chico, CA	65,008	1	44	45	46,438	2,885,701	2,932,139	98.4%
Huntsville, AL	143,254	2	44	46	258,827	6,338,358	6,597,185	96.1%
Knoxville, TN	275,253	3	44	47	849,223	12,166,691	13,015,913	93.5%
El Paso, TX	203,591	5	44	49	963,326	8,984,001	9,947,327	90.3%
Binghamton, NY	72,823	1	44	45	60,408	3,190,249	3,250,657	98.1%
Sacramento-Roseville-Folsom, CA	656,206	1	44	45	799,537	28,609,461	29,408,999	97.3%
California-Lexington Park, MD	35,784	16	42	58	554,674	1,518,255	2,072,929	73.2%
Lebanon, PA	44,842	1	42	43	39,718	1,869,759	1,909,477	97.9%
La Crosse-Onalaska, WI-MN	41,016	0	42	42	1,749	1,706,220	1,707,969	99.9%
Bloomington, IN	43,619	0	41	41	587	1,804,788	1,805,375	100.0%
Enid, OK	22,082	0	41	41	0	904,759	904,759	100.0%
Raleigh-Cary, NC	364,247	3	41	44	1,270,437	14,914,775	16,185,212	92.2%
East Stroudsburg, PA	72,215	3	41	44	231,181	2,948,213	3,179,394	92.7%
Seattle-Tacoma-Bellevue, WA	977,220	2	40	42	1,944,760	39,512,342	41,457,102	95.3%
Kokomo, IN	30,589	1	40	41	16,175	1,227,520	1,243,695	98.7%
Grand Rapids-Kentwood, MI	302,385	0	38	39	120,461	11,579,209	11,699,670	99.0%
Winchester, VA-WV	47,731	6	38	44	285,814	1,819,430	2,105,243	86.4%
Morristown, TN	43,904	3	38	41	113,287	1,672,916	1,786,204	93.7%
Orlando-Kissimmee-Sanford, FL	649,296	6	38	44	3,837,002	24,727,741	28,564,743	86.6%
Sioux Falls, SD	72,913	2	38	40	165,262	2,774,403	2,939,664	94.4%
Morgantown, WV	36,490	0	38	38	805	1,378,540	1,379,345	99.9%
Monroe, LA	61,946	15	38	53	927,394	2,328,909	3,256,303	71.5%
Hanford-Corcoran, CA	33,797	1	37	39	48,618	1,266,470	1,315,087	96.3%
The Villages, FL	54,399	3	37	41	180,611	2,026,457	2,207,067	91.8%
Carson City, NV	14,511	0	37	37	314	539,015	539,329	99.9%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1,830,424	3	37	41	6,260,544	67,981,752	74,242,296	91.6%
Fresno, CA	228,560	0	37	37	83,923	8,442,958	8,526,882	99.0%
Charlottesville, VA	68,445	9	37	46	598,446	2,525,150	3,123,596	80.8%
Mansfield, OH	41,810	1	37	38	42,067	1,542,151	1,584,218	97.3%
Casper, WY	25,316	1	37	38	30,361	930,483	960,844	96.8%
Clarksville, TN-KY	88,366	0	37	37	7,399	3,247,603	3,255,003	99.8%
Fayetteville, NC	148,194	1	37	38	167,866	5,432,293	5,600,159	97.0%
Wichita Falls, TX	48,810	3	37	39	141,586	1,784,560	1,926,146	92.6%
Salem, OR	105,347	2	36	38	213,412	3,834,466	4,047,878	94.7%
Chicago-Naperville-Elgin, IL-IN-WI	2,286,708	1	36	37	2,400,516	83,177,239	85,577,755	97.2%
Hattiesburg, MS	47,732	3	36	39	142,013	1,734,858	1,876,871	92.4%
Hinesville, GA	19,678	1	36	37	9,979	711,108	721,087	98.6%
Dover, DE	52,288	5	36	41	236,721	1,883,448	2,120,168	88.8%
Fond du Lac, WI	33,401	1	36	36	19,172	1,190,814	1,209,985	98.4%
Kingsport-Bristol, TN-VA	105,811	1	36	36	61,392	3,759,878	3,821,271	98.4%
Glens Falls, NY	51,715	0	35	36	12,856	1,835,844	1,848,699	99.3%
Atlantic City-Hammonton, NJ	84,496	21	35	56	1,771,480	2,990,459	4,761,940	62.8%
Modesto, CA	142,918	2	35	37	310,848	4,964,801	5,275,649	94.1%
Harrisburg-Carlisle, PA	186,174	3	35	38	607,417	6,428,487	7,035,904	91.4%
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,422,224	4	35	39	6,310,593	49,073,205	55,383,798	88.6%
Madison, WI	176,281	1	34	36	207,056	6,079,459	6,286,515	96.7%
Pine Bluff, AR	29,600	1	34	35	28,206	1,019,442	1,047,648	97.3%
Bellingham, WA	63,428	5	34	39	314,691	2,171,496	2,486,187	87.3%
Tallahassee, FL	100,908	20	34	54	2,046,654	3,440,387	5,487,041	62.7%
Wichita, KS	204,600	1	34	35	232,879	6,961,177	7,194,056	96.8%
Mankato, MN	28,115	0	34	34	203	956,509	956,712	100.0%
Sierra Vista-Douglas, AZ	39,847	6	34	40	237,405	1,348,469	1,585,874	85.0%
Goldsboro, NC	32,604	1	34	35	33,811	1,103,310	1,137,122	97.0%
Yuma, AZ	49,526	3	34	36	127,443	1,662,932	1,790,375	92.9%
Albuquerque, NM	276,350	0	33	33	122,720	9,025,177	9,147,897	98.7%
Hagerstown-Martinsburg, MD-WV	92,244	2	33	35	189,775	3,010,082	3,199,856	94.1%
Tuscaloosa, AL	68,453	1	32	34	98,300	2,211,896	2,310,196	95.7%
Jonesboro, AR	39,234	0	32	32	537	1,267,508	1,268,045	100.0%
Salt Lake City, UT	287,230	0	32	32	4,105	9,212,188	9,216,294	100.0%
Fort Smith, AR-OK	80,750	2	32	34	171,402	2,585,504	2,756,906	93.8%
Auburn-Opelika, AL	38,939	0	31	32	11,582	1,224,208	1,235,790	99.1%
Parkersburg-Vienna, WV	33,885	6	31	37	187,370	1,062,828	1,250,198	85.0%
Decatur, AL	48,947	1	31	32	30,642	1,531,898	1,562,540	98.0%
Rocky Mount, NC	43,642	1	31	32	49,792	1,344,525	1,394,317	96.4%
Jefferson City, MO	48,069	5	31	35	218,815	1,477,494	1,696,309	87.1%
Jackson, MS	178,657	2	30	32	318,305	5,420,959	5,739,265	94.5%
Rome, GA	29,822	2	30	32	49,590	897,802	947,392	94.8%
Johnstown, PA	53,643	2	30	32	103,328	1,613,678	1,717,005	94.0%
Odessa, TX	36,482	6	30	36	233,414	1,095,134	1,328,548	82.4%
Sheboygan, WI	35,338	0	30	30	0	1,051,075	1,051,075	100.0%
Victoria, TX	28,475	1	30	31	34,762	841,296	876,059	96.0%
Farmington, NM	30,322	0	30	30	26	895,179	895,206	100.0%
Owensboro, KY	38,253	1	29	30	28,508	1,112,196	1,140,704	97.5%

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Metropolitan Statistical Area Title (Note 1)	Single Family Residences (Note 1)	Average Annual Losses Insured (Note 2)	Uninsured (Note 2)	Total (Note 2)	Annual Losses Insured = (2) * (3)	Uninsured = (2) * (4)	Total = (5) + (6)	Percent of Losses Uninsured = (6) / (7)
Springfield, MO	151,362	2	29	31	294,621	4,397,124	4,691,745	93.7%
Albany-Schenectady-Troy, NY	243,598	2	29	31	443,180	7,068,891	7,512,071	94.1%
Grand Junction, CO	48,184	0	29	29	8,314	1,396,021	1,404,336	99.4%
Tulsa, OK	311,486	1	29	30	206,192	9,005,964	9,212,156	97.8%
Dallas-Fort Worth-Arlington, TX	1,774,642	3	28	32	5,713,468	50,555,812	56,269,280	89.8%
Eau Claire, WI	52,052	0	28	28	2,093	1,477,808	1,479,901	99.9%
Jackson, TN	61,377	0	28	28	2,354	1,740,277	1,742,631	99.9%
Lansing-East Lansing, MI	170,090	1	28	29	186,394	4,804,856	4,991,250	96.3%
Hickory-Lenoir-Morganton, NC	112,229	3	28	31	289,500	3,151,409	3,440,909	91.6%
Idaho Falls, ID	40,678	0	28	28	0	1,141,355	1,141,355	100.0%
Cleveland, TN	37,264	0	28	28	959	1,041,016	1,041,975	99.9%
Columbus, OH	587,034	1	28	28	532,251	16,186,391	16,718,642	96.8%
Blacksburg-Christiansburg, VA	47,600	18	27	46	871,150	1,305,687	2,176,837	60.0%
Terre Haute, IN	63,600	3	27	31	214,466	1,741,337	1,955,803	89.0%
Greenville-Anderson, SC	259,626	8	27	35	2,098,696	7,050,206	9,148,901	77.1%
Ann Arbor, MI	94,907	0	27	27	2,336	2,566,434	2,568,770	99.9%
Omaha-Council Bluffs, NE-IA	284,447	0	27	27	43,071	7,690,637	7,733,708	99.4%
Worcester, MA-CT	242,324	1	27	28	141,537	6,543,531	6,685,068	97.9%
El Centro, CA	38,508	1	27	28	30,355	1,038,890	1,069,245	97.2%
Laredo, TX	55,325	6	27	33	312,234	1,490,884	1,803,118	82.7%
Saginaw, MI	68,876	1	27	27	35,097	1,855,129	1,890,225	98.1%
Augusta-Richmond County, GA-SC	179,180	2	27	29	379,153	4,824,769	5,203,922	92.7%
Gettysburg, PA	34,673	0	27	27	5,824	928,257	934,082	99.4%
Elkhart-Goshen, IN	58,286	10	27	37	607,532	1,558,758	2,166,290	72.0%
Champaign-Urbana, IL	60,883	0	27	27	2,792	1,619,582	1,622,374	99.8%
Lewiston, ID-WA	19,993	1	26	27	20,101	528,525	548,626	96.3%
Minneapolis-St. Paul-Bloomington, MN-WI	1,021,609	1	26	27	569,651	26,711,165	27,280,816	97.9%
Florence-Muscle Shoals, AL	53,242	4	26	31	235,210	1,391,748	1,626,957	85.5%
Lancaster, PA	157,703	7	26	33	1,028,179	4,120,851	5,149,030	80.0%
Indianapolis-Carmel-Anderson, IN	634,827	1	26	27	858,778	16,464,041	17,322,819	95.0%
Charlotte-Concord-Gastonia, NC-SC	728,959	4	26	30	2,702,463	18,893,738	21,596,201	87.5%
Cincinnati, OH-KY-IN	656,376	0	26	26	283,382	16,828,298	17,111,680	98.3%
Niles, MI	60,741	0	26	26	64	1,549,685	1,549,749	100.0%
Bloomington, IL	47,664	0	25	25	684	1,211,399	1,212,084	99.9%
Atlanta-Sandy Springs-Alpharetta, GA	1,621,740	2	25	27	2,485,022	40,784,706	43,269,728	94.3%
Providence-Warwick, RI-MA	404,392	4	25	29	1,539,531	10,168,692	11,708,224	86.9%
Joplin, MO	60,391	6	25	31	354,509	1,512,491	1,867,000	81.0%
Columbia, SC	235,164	4	25	29	1,042,109	5,873,176	6,915,285	84.9%
Utica-Rome, NY	89,908	1	25	26	124,586	2,215,031	2,339,617	94.7%
Albany, GA	42,795	2	25	26	79,161	1,052,893	1,132,054	93.0%
York-Hanover, PA	146,752	1	25	26	207,109	3,608,997	3,816,106	94.6%
Durham-Chapel Hill, NC	176,197	2	24	26	311,514	4,309,944	4,621,457	93.3%
Kansas City, MO-KS	684,093	1	24	25	665,309	16,602,317	17,267,626	96.1%
Pueblo, CO	55,343	0	24	24	451	1,342,872	1,343,324	100.0%
South Bend-Mishawaka, IN-MI	111,987	0	24	24	5,421	2,712,906	2,718,327	99.8%
Richmond, VA	390,291	4	24	28	1,597,396	9,229,702	10,827,098	85.2%
Macon-Bibb County, GA	70,206	1	23	24	83,400	1,631,034	1,714,435	95.1%
Dalton, GA	35,740	1	23	24	24,165	829,595	853,761	97.2%
Birmingham-Hoover, AL	348,098	1	23	24	397,704	8,055,312	8,453,016	95.3%
Olympia-Lacey-Tumwater, WA	81,895	2	23	25	174,067	1,886,079	2,060,146	91.6%
Colorado Springs, CO	210,551	0	23	23	21,183	4,839,676	4,860,859	99.6%
Lakeland-Winter Haven, FL	183,132	4	23	27	656,094	4,200,766	4,856,860	86.5%
Logan, UT-ID	32,839	0	23	23	0	750,229	750,229	100.0%
Green Bay, WI	101,075	0	23	23	7,394	2,296,619	2,304,013	99.7%
Spartanburg, SC	89,595	3	23	25	249,447	2,033,145	2,282,592	89.1%
Pittsburgh, PA	848,872	2	22	24	1,429,786	18,987,968	20,417,754	93.0%
Denver-Aurora-Lakewood, CO	769,541	0	22	23	234,889	17,116,733	17,351,622	98.6%
Walla Walla, WA	17,451	1	22	23	16,771	379,492	396,263	95.8%
Canton-Massillon, OH	140,756	0	22	22	28,422	3,058,414	3,086,836	99.1%
Provo-Orem, UT	126,241	0	22	22	470	2,737,920	2,738,390	100.0%
Detroit-Warren-Dearborn, MI	1,460,406	0	22	22	545,185	31,666,096	32,211,281	98.3%
Oshkosh-Neenah, WI	52,178	1	22	23	66,363	1,127,390	1,193,753	94.4%
Ames, IA	31,807	0	21	22	2,007	683,400	685,408	99.7%
Lima, OH	34,734	0	21	21	356	740,920	741,277	100.0%
Racine, WI	59,802	0	21	21	0	1,252,923	1,252,923	100.0%
Fort Wayne, IN	131,241	0	21	21	17,398	2,744,139	2,761,538	99.4%
Pocatello, ID	26,373	3	21	24	84,814	548,023	632,837	86.6%
Florence, SC	57,428	2	21	23	120,186	1,192,909	1,313,094	90.8%
Memphis, TN-MS-AR	408,730	0	21	21	141,057	8,478,334	8,619,391	98.4%
Columbus, IN	25,959	1	21	22	36,831	532,505	569,336	93.5%
Reading, PA	132,322	0	20	20	2,893	2,698,490	2,701,383	99.9%
Rockford, IL	110,588	3	20	24	377,319	2,247,550	2,624,869	85.6%
Davenport-Moline-Rock Island, IA-IL	129,399	1	20	21	113,171	2,628,222	2,741,393	95.9%
Jackson, MI	54,228	4	20	24	192,639	1,099,469	1,292,108	85.1%
Battle Creek, MI	45,127	2	20	22	69,009	907,318	976,327	92.9%

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Metropolitan	Single Family	Average Annual Losses			Annual Losses			Percent of
Statistical Area Title	Residences	Insured	Uninsured	Total	Insured	Uninsured	Total	Losses Uninsured
(Note 1)	(Note 1)	(Note 2)	(Note 2)	(Note 2)	= (2) * (3)	= (2) * (4)	= (5) + (6)	= (6) / (7)
Waterloo-Cedar Falls, IA	55,780	1	20	22	80,198	1,121,261	1,201,459	93.3%
Montgomery, AL	120,952	1	20	21	174,425	2,413,565	2,587,990	93.3%
Roanoke, VA	110,383	4	20	24	449,906	2,196,652	2,646,557	83.0%
Kalamazoo-Portage, MI	75,706	1	20	20	40,525	1,499,968	1,540,493	97.4%
Iowa City, IA	44,474	0	20	20	355	878,660	879,015	100.0%
Buffalo-Cheektowaga, NY	332,833	1	20	20	197,352	6,566,156	6,763,508	97.1%
Baltimore-Columbia-Towson, MD	854,053	2	20	22	1,939,484	16,822,420	18,761,905	89.7%
Sumter, SC	40,739	1	19	21	49,706	793,718	843,423	94.1%
Burlington-South Burlington, VT	62,176	0	19	20	4,253	1,210,595	1,214,848	99.6%
Topeka, KS	81,230	0	19	20	11,199	1,578,420	1,589,619	99.3%
Killeen-Temple, TX	120,075	4	19	24	515,933	2,315,660	2,831,592	81.8%
Lubbock, TX	90,532	1	19	20	118,575	1,728,972	1,847,547	93.6%
Sherman-Denison, TX	41,011	4	19	23	150,358	781,287	931,645	83.9%
Monroe, MI	50,428	1	19	19	26,625	947,324	973,949	97.3%
Amarillo, TX	79,013	3	19	21	202,470	1,482,289	1,684,759	88.0%
Cheyenne, WY	30,839	0	18	18	0	569,781	569,781	100.0%
San Angelo, TX	36,544	8	18	26	290,016	674,089	964,105	69.9%
Toledo, OH	218,588	1	18	19	138,720	4,018,662	4,157,383	96.7%
Akron, OH	234,472	0	18	18	27,532	4,301,140	4,328,672	99.4%
Milwaukee-Waukesha, WI	411,667	1	18	19	268,019	7,551,029	7,819,047	96.6%
Des Moines-West Des Moines, IA	205,997	0	18	18	41,921	3,750,400	3,792,321	98.9%
Janesville-Beloit, WI	54,098	0	18	18	20,898	977,172	998,070	97.9%
Cleveland-Elyria, OH	677,248	0	18	18	201,686	12,187,318	12,389,003	98.4%
Peoria, IL	147,423	1	18	19	175,275	2,651,628	2,826,903	93.8%
Coeur d'Alene, ID	52,479	0	18	18	11,899	942,558	954,457	98.8%
Cedar Rapids, IA	86,691	1	18	19	71,984	1,546,661	1,618,644	95.6%
Abilene, TX	52,367	11	18	28	569,116	916,955	1,486,072	61.7%
St. Joseph, MO-KS	40,909	0	18	18	0	716,206	716,206	100.0%
Bay City, MI	39,105	0	18	18	15,510	684,492	700,002	97.8%
Texarkana, TX-AR	45,409	1	17	19	54,104	790,435	844,539	93.6%
St. Cloud, MN	59,257	0	17	17	1,826	1,015,233	1,017,058	99.8%
Kankakee, IL	33,518	3	17	20	110,437	571,015	681,452	83.8%
Lawrence, KS	31,544	0	17	17	170	527,433	527,603	100.0%
Athens-Clarke County, GA	52,572	0	16	17	4,079	864,774	868,853	99.5%
Evansville, IN-KY	105,358	0	16	17	46,199	1,705,242	1,751,441	97.4%
Spokane-Spokane Valley, WA	164,094	0	16	16	3,244	2,636,545	2,639,788	99.9%
Carbondale-Marion, IL	43,934	1	16	17	54,441	704,436	758,877	92.8%
Lincoln, NE	92,442	2	16	18	168,971	1,455,174	1,624,145	89.6%
Shreveport-Bossier City, LA	125,017	7	16	23	929,308	1,959,533	2,888,842	67.8%
Erie, PA	84,024	0	16	16	9,545	1,311,910	1,321,454	99.3%
Wausau-Weston, WI	59,358	0	15	16	3,454	919,813	923,267	99.6%
Flint, MI	151,736	0	15	16	31,787	2,349,675	2,381,462	98.7%
Columbus, GA-AL	93,899	0	15	16	22,693	1,447,115	1,469,808	98.5%
Dothan, AL	47,577	1	15	16	46,289	726,990	773,278	94.0%
Ogden-Clearfield, UT	172,515	0	15	15	4,119	2,614,870	2,618,989	99.8%
Gadsden, AL	36,804	2	15	17	56,867	554,724	611,591	90.7%
Bangor, ME	50,205	0	15	15	145	743,529	743,674	100.0%
Anniston-Oxford, AL	38,862	1	15	16	30,032	572,751	602,783	95.0%
Elmira, NY	26,845	2	14	16	46,500	386,456	432,956	89.3%
Longview, TX	81,840	2	14	17	182,078	1,177,978	1,360,056	86.6%
Tyler, TX	63,608	11	14	26	719,760	913,389	1,633,148	55.9%
Lewiston-Auburn, ME	29,970	0	14	14	2,421	430,066	432,486	99.4%
Dayton-Kettering, OH	279,295	1	14	15	195,622	3,971,131	4,166,754	95.3%
Waco, TX	75,051	3	14	17	203,991	1,055,573	1,259,564	83.8%
Lynchburg, VA	84,920	1	14	15	112,134	1,190,093	1,302,227	91.4%
Rochester, NY	336,611	1	14	15	304,380	4,674,354	4,978,734	93.9%
Greeley, CO	79,934	0	14	14	3,307	1,102,650	1,105,957	99.7%
Gainesville, GA	53,339	0	14	14	15,713	732,136	747,850	97.9%
Twin Falls, ID	32,550	0	14	14	0	443,675	443,675	100.0%
Columbia, MO	56,885	4	13	17	219,596	765,548	985,144	77.7%
Burlington, NC	48,979	2	13	15	99,490	638,991	738,481	86.5%
Decatur, IL	40,256	0	13	13	695	511,751	512,446	99.9%
Duluth, MN-WI	116,086	0	13	13	1,238	1,468,798	1,470,036	99.9%
Kennewick-Richland, WA	68,776	1	13	13	38,210	864,610	902,820	95.8%
Springfield, IL	74,628	3	12	16	249,974	924,028	1,174,001	78.7%
Syracuse, NY	198,727	2	12	14	319,805	2,444,632	2,764,437	88.4%
Muncie, IN	39,461	2	12	14	91,840	475,843	567,683	83.8%
Manhattan, KS	33,736	0	12	12	0	404,203	404,203	100.0%
Winston-Salem, NC	211,621	2	12	13	382,375	2,470,251	2,852,626	86.6%
Greensboro-High Point, NC	227,029	2	12	14	476,273	2,633,702	3,109,975	84.7%
Dubuque, IA	30,136	0	11	11	2,391	336,163	338,553	99.3%
Valdosta, GA	39,704	2	11	13	89,315	435,377	524,692	83.0%
Youngstown-Warren-Boardman, OH-PA	204,258	0	11	11	8,588	2,218,863	2,227,451	99.6%
Appleton, WI	73,979	0	10	10	9	772,646	772,655	100.0%
Vineland-Bridgeton, NJ	40,871	9	10	19	380,503	407,564	788,067	51.7%

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Metropolitan	Single Family	Average Annual Losses			Annual Losses			Percent of
Statistical Area Title	Residences	Insured	Uninsured	Total	Insured	Uninsured	Total	Losses Uninsured
(Note 1)	(Note 1)	(Note 2)	(Note 2)	(Note 2)	= (2) * (3)	= (2) * (4)	= (5) + (6)	= (6) / (7)
Springfield, OH	48,584	0	10	10	308	463,692	464,000	99.9%
Watertown-Fort Drum, NY	37,853	0	9	9	5,458	351,501	356,959	98.5%
Warner Robins, GA	54,033	2	9	11	84,896	493,155	578,051	85.3%
Danville, IL	28,655	0	9	9	2,192	256,246	258,437	99.2%
Bremerton-Silverdale-Port Orchard, WA	81,736	0	8	8	2,800	635,800	638,600	99.6%
Total All MSAs	74,570,040	$10	$70	$80	$766,115,468	$5,188,121,769	$5,954,237,237	87.1%
Total Outside MSAs	16,212,126	$7	$61	$68	$110,374,631	$989,912,415	$1,100,287,046	90.0%
Total	90,782,166	$10	$68	$78	$876,490,099	$6,178,034,184	$7,054,524,283	87.6%

Notes:

1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Columns (3) to (5) contain loss data that from KatRisk catastrophe model runs on a subset of Milliman market basket locations. Modeling runs were set to a standard sea level rise scenario.
3. Insured and Uninsured Losses are based on estimates of NFIP take-up rates and coverages.

Exhibit 9: Change in Storm Surge Losses for Sea Level Rise Scenarios Compared to Current

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Single Family Residences Exposed to Storm Surge, Current Scenario	Percent Increase in Single Family Residences Exposed to Storm Surge		Percent Increase in Storm Surge Uninsured Loss		Percent Increase in Storm Surge Loss	
Metropolitan Statistical Area Name (Note 1)	Single Family Residences (Note 1)	(Note 2)	Medium Sea Level Rise vs. Current Sea Level (Note 3)	High Sea Level Rise vs. Current Sea Level (Note 4)	Medium Sea Level Rise vs. Current Sea Level (Note 5)	High Sea Level Rise vs. Current Sea Level (Note 6)	Medium Sea Level Rise vs. Current Sea Level (Note 7)	High Sea Level Rise vs. Current Sea Level (Note 8)
Atlantic City-Hammonton, NJ	84,496	30,099	1.0%	3.0%	46.7%	189.4%	50.6%	203.2%
Corpus Christi, TX	121,799	35,100	7.7%	12.3%	48.3%	109.0%	49.1%	111.2%
Orlando-Kissimmee-Sanford, FL	649,296	400	25.0%	50.0%	46.9%	116.4%	48.5%	156.2%
Salisbury, MD-DE	161,632	61,074	3.4%	7.2%	47.0%	177.7%	46.8%	174.8%
Ocean City, NJ	75,589	64,290.64	2.6%	5.6%	43.1%	152.4%	42.9%	150.7%
California-Lexington Park, MD	35,784	4,598	0.0%	8.7%	21.9%	94.2%	36.8%	155.3%
Baltimore-Columbia-Towson, MD	854,053	33,298	4.5%	15.3%	34.7%	151.2%	34.6%	149.0%
Houma-Thibodaux, LA	60,417	60,417	0.0%	0.0%	33.8%	77.9%	33.6%	77.2%
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,422,224	6,899	5.8%	11.6%	34.2%	127.2%	33.5%	125.5%
Brunswick, GA	37,880	28,785	0.3%	1.7%	32.0%	100.5%	32.0%	100.2%
Vineland-Bridgeton, NJ	40,871	6,096	3.3%	4.9%	14.8%	53.8%	31.8%	107.4%
Virginia Beach-Norfolk-Newport News, VA-NC	523,327	323,017	3.3%	6.0%	30.4%	103.3%	31.0%	105.7%
New Bern, NC	41,778	21,189	2.4%	9.4%	28.1%	97.2%	29.3%	99.9%
Charleston-North Charleston, SC	212,033	102,416	1.8%	3.5%	30.1%	96.9%	28.8%	92.1%
Savannah, GA	109,497	78,898	2.3%	5.7%	28.1%	89.9%	28.2%	90.3%
Dover, DE	52,288	2,399	4.2%	12.5%	27.6%	87.4%	28.0%	88.8%
New York-Newark-Jersey City, NY-NJ-PA	3,262,366	340,686	2.4%	7.0%	26.9%	101.2%	27.3%	102.5%
Jacksonville, FL	429,019	101,404	3.6%	10.0%	26.6%	87.8%	27.1%	89.0%
Lafayette, LA	141,177	120,065	1.4%	2.6%	25.6%	52.7%	25.1%	51.4%
Hinesville, GA	19,678	4,595	0.0%	2.2%	23.4%	69.1%	23.5%	69.4%
Sebastian-Vero Beach, FL	52,438	8,906	4.5%	11.2%	23.8%	80.4%	23.5%	79.0%
Providence-Warwick, RI-MA	404,392	18,704	3.7%	13.4%	22.3%	95.9%	23.4%	100.3%
Norwich-New London, CT	85,235	8,503	3.5%	11.8%	23.4%	95.5%	23.3%	93.4%
Richmond, VA	390,291	1,800	11.1%	22.2%	26.9%	82.9%	23.3%	74.1%
Deltona-Daytona Beach-Ormond Beach, FL	220,757	76,920	0.5%	1.7%	21.9%	70.9%	22.1%	71.9%
Barnstable Town, MA	138,885	25,497	3.5%	9.0%	21.6%	81.0%	22.1%	82.7%
Miami-Fort Lauderdale-Pompano Beach, FL	1,292,465	477,787	3.0%	7.5%	22.4%	66.5%	22.1%	65.4%
Lake Charles, LA	62,822	59,721	0.0%	0.0%	22.2%	49.6%	22.1%	49.2%
Panama City, FL	55,465	16,290	7.4%	20.9%	21.2%	84.6%	21.2%	84.1%
Hartford-East Hartford-Middletown, CT	332,941	6,601	1.5%	3.0%	21.4%	80.4%	20.8%	77.8%
Port St. Lucie, FL	147,959	20,094	9.0%	28.9%	21.8%	76.2%	20.6%	70.2%
Bridgeport-Stamford-Norwalk, CT	238,970	12,598	4.0%	5.6%	21.4%	84.7%	20.6%	81.2%
Baton Rouge, LA	241,791	90,134	1.4%	3.6%	19.5%	50.3%	20.4%	52.9%
Naples-Marco Island, FL	95,685	94,485	0.0%	0.1%	21.1%	60.1%	20.2%	56.9%
Boston-Cambridge-Newton, MA-NH	1,042,909	36,597	4.6%	13.7%	20.0%	79.2%	19.5%	76.2%
Crestview-Fort Walton Beach-Destin, FL	92,891	23,598	5.9%	12.7%	19.1%	72.2%	19.3%	72.5%
Brownsville-Harlingen, TX	98,581	38,593	6.7%	10.6%	18.5%	42.7%	19.3%	44.5%
Cape Coral-Fort Myers, FL	238,495	225,495	0.2%	0.8%	19.4%	54.0%	18.9%	52.4%
New Haven-Milford, CT	213,870	18,397	1.6%	6.0%	18.7%	68.6%	18.6%	68.5%
Palm Bay-Melbourne-Titusville, FL	190,403	48,301	1.7%	3.7%	18.2%	57.1%	18.6%	58.4%
Wilmington, NC	93,347	19,489	4.1%	13.3%	18.1%	62.9%	18.2%	62.8%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	156,898	40,099	2.7%	10.0%	18.6%	63.4%	18.2%	61.8%
Hilton Head Island-Bluffton, SC	72,147	55,836	1.8%	5.6%	17.8%	52.3%	17.9%	52.6%
Houston-The Woodlands-Sugar Land, TX	1,649,856	321,730	1.1%	2.3%	17.5%	42.2%	17.6%	42.8%
North Port-Sarasota-Bradenton, FL	263,971	158,183	2.0%	5.5%	17.0%	58.2%	17.3%	59.1%
Punta Gorda, FL	70,708	70,308	0.0%	0.4%	17.0%	48.2%	17.2%	48.5%
Pensacola-Ferry Pass-Brent, FL	151,893	15,199	3.9%	11.2%	15.1%	55.1%	16.9%	62.3%
Tampa-St. Petersburg-Clearwater, FL	849,853	285,451	1.3%	3.5%	16.0%	53.6%	16.5%	55.1%
Beaumont-Port Arthur, TX	120,529	105,425	0.0%	0.2%	16.5%	36.6%	16.4%	36.4%
Daphne-Fairhope-Foley, AL	70,318	14,404	0.7%	1.4%	15.4%	55.3%	16.1%	58.5%
Jacksonville, NC	53,490	6,799	5.9%	10.3%	16.6%	51.8%	15.5%	47.4%
Portland-South Portland, ME	193,001	5,804	3.6%	14.5%	15.5%	65.1%	15.2%	63.7%
Gainesville, FL	75,798	1,700	0.0%	0.0%	15.6%	43.8%	15.1%	42.9%
Gulfport-Biloxi, MS	130,147	92,462	0.2%	0.3%	14.9%	44.6%	14.9%	44.6%
Mobile, AL	139,996	29,399	3.1%	9.5%	14.8%	44.0%	14.6%	43.4%
Homosassa Springs, FL	55,727	11,906	0.8%	0.8%	14.3%	43.5%	14.2%	43.2%
Tallahassee, FL	100,908	8,292	0.0%	2.4%	12.1%	33.3%	12.2%	33.6%
New Orleans-Metairie, LA	371,993	359,590	0.0%	0.2%	12.1%	27.8%	11.4%	26.1%
Hammond, LA	34,396	15,198	5.3%	8.6%	12.8%	31.8%	11.1%	29.1%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1,830,424	67,497	7.0%	15.6%	6.0%	33.2%	6.5%	32.7%
Kingston, NY	61,429	100	0.0%	100.0%	27.1%	749.8%	4.7%	86.1%
Greenville, NC	44,156	400	0.0%	50.0%	0.2%	1.7%	0.3%	1.9%
Total All MSAs	74,520,514	4,420,220	2.0%	4.9%	21.0%	65.0%	20.9%	64.5%
Total Outside MSAs	16,212,126	265,317	2.2%	5.1%	28.9%	86.8%	28.5%	86.0%
Total	90,732,640	4,685,537	2.0%	5.0%	21.4%	66.1%	21.3%	65.7%

Notes:
1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Column (3) = Exhibit 10 Column (4)
3. Column (4) = (Exhibit 11 Column (4) – Exhibit 10 Column (4)) / Exhibit 10 Column (4)
4. Column (5) = (Exhibit 12 Column (4) – Exhibit 10 Column (4)) / Exhibit 10 Column (4)
5. Column (6) = (Exhibit 11 Column (8) – Exhibit 10 Column (8)) / Exhibit 10 Column (8). Insured and Uninsured Losses are based on estimates of NFIP take-up rates and coverages.
6. Column (7) = (Exhibit 12 Column (8) – Exhibit 10 Column (8)) / Exhibit 10 Column (8). Insured and Uninsured Losses are based on estimates of NFIP take-up rates and coverages.
7. Column (8) = (Exhibit 11 Column (9) – Exhibit 10 Column (9)) / Exhibit 10 Column (9)
8. Column (9) = (Exhibit 12 Column (9) – Exhibit 10 Column (9)) / Exhibit 10 Column (9)

Exhibit 10: Storm Surge Losses by MSA - Current Sea Levels

(1) Metropolitan Statistical Area Name (Note 1)	(2) Single Family Residences (Note 1)	(3) Percent of Single Family Residences Exposed to Storm Surge (Note 2)	(4) Single Family Residences Exposed to Storm Surge (Note 3)	(5) Average Annual Storm Surge Insured Losses (Note 4)	(6) Average Annual Storm Surge Uninsured Losses (Note 4)	(7) Total Annual Storm Surge Insured Losses = (4) * (5)	(8) Total Annual Storm Surge Uninsured Losses = (4) * (6)	(9) Total Annual Storm Surge Losses = (7) + (8)	(10) Percent of Storm Surge Losses Uninsured = (8) / (9)
New Orleans-Metairie, LA	371,993	96.7%	359,590	$183	$533	$65,676,785	$191,826,500	$257,503,284	74%
Miami-Fort Lauderdale-Pompano Beach, FL	1,292,465	37.0%	477,787	126	369	59,975,377	176,068,959	236,044,336	75%
New York-Newark-Jersey City, NY-NJ-PA	3,262,366	10.4%	340,686	127	479	43,196,373	163,172,697	206,369,069	79%
Cape Coral-Fort Myers, FL	238,495	94.5%	225,495	284	563	63,962,263	126,892,431	190,854,694	66%
Hilton Head Island-Bluffton, SC	72,147	77.4%	55,836	291	2,272	16,249,038	126,876,180	143,125,219	89%
Tampa-St. Petersburg-Clearwater, FL	849,853	33.6%	285,451	146	248	41,645,688	70,824,114	112,469,802	63%
Houston-The Woodlands-Sugar Land, TX	1,649,856	19.5%	321,730	29	300	9,351,423	96,477,511	105,828,935	91%
Naples-Marco Island, FL	95,685	98.7%	94,485	362	662	34,168,067	62,573,515	96,741,581	65%
Punta Gorda, FL	70,708	99.4%	70,308	352	616	24,735,052	43,287,792	68,022,843	64%
Charleston-North Charleston, SC	212,033	48.3%	102,416	195	395	19,920,847	40,405,905	60,326,752	67%
Jacksonville, FL	429,019	23.6%	101,404	118	450	11,932,615	45,583,548	57,516,163	79%
Houma-Thibodaux, LA	60,417	100.0%	60,417	257	667	15,553,261	40,322,766	55,876,027	72%
North Port-Sarasota-Bradenton, FL	263,971	59.9%	158,183	120	225	18,979,822	35,590,809	54,570,631	65%
Virginia Beach-Norfolk-Newport News, VA-NC	523,327	61.7%	323,017	35	121	11,422,922	39,012,630	50,435,552	77%
Ocean City, NJ	75,589	85.1%	64,291	195	517	12,510,098	33,221,645	45,731,744	73%
Boston-Cambridge-Newton, MA-NH	1,042,909	3.5%	36,597	199	971	7,271,034	35,545,426	42,816,460	83%
Beaumont-Port Arthur, TX	120,529	87.5%	105,425	36	364	3,747,084	38,328,495	42,075,579	91%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	156,898	25.6%	40,099	230	474	9,207,030	18,995,587	28,202,616	67%
Lafayette, LA	141,177	85.0%	120,065	83	131	9,950,321	15,732,642	25,682,963	61%
Sebastian-Vero Beach, FL	52,438	17.0%	8,906	171	2,500	1,527,440	22,268,952	23,796,391	94%
Jacksonville, NC	53,490	12.7%	6,799	1,034	2,279	7,029,454	15,491,426	22,520,880	69%
Deltona-Daytona Beach-Ormond Beach, FL	220,757	34.8%	76,920	70	208	5,372,068	15,963,444	21,335,512	75%
Lake Charles, LA	62,822	95.1%	59,721	108	227	6,451,543	13,574,303	20,025,846	68%
Portland-South Portland, ME	193,001	3.0%	5,804	209	3,132	1,214,294	18,176,396	19,390,690	94%
Palm Bay-Melbourne-Titusville, FL	190,403	25.4%	48,301	38	361	1,852,033	17,430,437	19,282,470	90%
Bridgeport-Stamford-Norwalk, CT	238,970	5.3%	12,598	263	1,119	3,318,801	14,097,575	17,416,377	81%
Wilmington, NC	93,347	20.9%	19,489	170	708	3,307,824	13,796,429	17,104,253	81%
Gulfport-Biloxi, MS	130,147	71.0%	92,462	30	149	2,729,900	13,803,842	16,533,742	83%
New Haven-Milford, CT	213,870	8.6%	18,397	127	730	2,338,065	13,437,334	15,775,399	85%
Salisbury, MD-DE	161,632	37.8%	61,074	96	130	5,880,899	7,930,213	13,811,112	57%
Port St. Lucie, FL	147,959	13.6%	20,094	208	421	4,185,044	8,453,749	12,638,794	67%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1,830,424	3.7%	67,497	41	141	2,763,814	9,535,125	12,298,939	78%
Baton Rouge, LA	241,791	37.3%	90,134	51	82	4,575,227	7,375,051	11,950,278	62%
Homosassa Springs, FL	55,727	21.4%	11,906	337	618	4,010,747	7,362,398	11,373,145	65%
Barnstable Town, MA	138,885	18.4%	25,497	32	390	816,343	9,956,553	10,772,895	92%
Savannah, GA	109,497	72.1%	78,898	19	117	1,526,499	9,223,203	10,749,702	86%
Mobile, AL	139,996	21.0%	29,399	54	304	1,585,854	8,937,413	10,523,266	85%
Daphne-Fairhope-Foley, AL	70,318	20.5%	14,404	80	646	1,149,824	9,301,685	10,451,509	89%
Brunswick, GA	37,880	76.0%	28,785	33	223	964,260	6,416,524	7,380,784	87%
Crestview-Fort Walton Beach-Destin, FL	92,891	25.4%	23,598	68	196	1,612,384	4,632,408	6,244,792	74%
Hartford-East Hartford-Middletown, CT	332,941	2.0%	6,601	138	708	910,798	4,674,313	5,585,111	84%
Corpus Christi, TX	121,799	28.8%	35,100	13	114	460,554	4,009,256	4,469,810	90%
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,422,224	0.5%	6,899	20	594	140,188	4,097,234	4,237,422	97%
Atlantic City-Hammonton, NJ	84,496	35.6%	30,099	56	82	1,688,498	2,477,984	4,166,482	59%
New Bern, NC	41,778	50.7%	21,189	45	139	954,171	2,953,738	3,907,908	76%
Pensacola-Ferry Pass-Brent, FL	151,893	10.0%	15,199	77	167	1,173,628	2,543,037	3,716,665	68%
Brownsville-Harlingen, TX	98,581	39.1%	38,593	9	85	356,609	3,282,949	3,639,559	90%
Norwich-New London, CT	85,235	10.0%	8,503	89	336	755,231	2,860,894	3,616,125	79%
Panama City, FL	55,465	29.4%	16,290	33	122	543,940	1,993,770	2,537,710	79%
Tallahassee, FL	100,908	8.2%	8,292	156	148	1,296,648	1,231,196	2,527,844	49%
Baltimore-Columbia-Towson, MD	854,053	3.9%	33,298	14	52	468,141	1,725,498	2,193,639	79%
Hammond, LA	34,396	44.2%	15,198	46	74	696,574	1,130,015	1,826,589	62%
Providence-Warwick, RI-MA	404,392	4.6%	18,704	20	74	374,995	1,377,582	1,752,578	79%
Gainesville, FL	75,798	2.2%	1,700	244	359	414,699	611,008	1,025,707	60%
Dover, DE	52,288	4.6%	2,399	60	284	144,956	681,484	826,439	82%
California-Lexington Park, MD	35,784	12.8%	4,598	83	45	380,407	204,718	585,125	35%
Hinesville, GA	19,678	23.4%	4,595	2	117	7,194	537,063	544,257	99%
Vineland-Bridgeton, NJ	40,871	14.9%	6,096	62	26	380,331	161,218	541,549	30%
Bangor, ME	50,205	0.4%	200	0	459	0	91,787	91,787	100%
Orlando-Kissimmee-Sanford, FL	649,296	0.1%	400	187	9	74,856	3,720	78,576	5%
Richmond, VA	390,291	0.5%	1,800	6	24	11,138	43,070	54,208	79%
Greenville, NC	44,156	0.9%	400	8	72	3,081	28,891	31,972	90%
Kingston, NY	61,429	0.2%	100	207	10	20,685	1,034	21,719	5%
Total All MSAs	74,570,040	5.9%	4,420,220	$126	$381	$554,924,738	$1,684,625,068	$2,239,549,806	75%
Total Outside MSAs	16,212,126	1.6%	265,317	173	343	45,920,279	90,934,090	136,854,369	66%
Total	90,782,166	5.2%	4,685,537	128	379	600,845,017	1,775,559,158	2,376,404,175	75%

Notes:
1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Any given location is deemed to have storm surge exposure if its combined inland flood and storm surge ground up loss is greater than its inland flood loss alone.
3. Column (4) = Column (2) * Column (3).
4. Loss data is ground up storm surge losses sourced KatRisk catastrophe model runs on a subset of Milliman market basket locations. Modeling runs were set to a standard sea level rise scenario
5. Insured and Uninsured losses are based on estimates of NFIP take-up rates and coverages.

Exhibit 11: Storm Surge Losses by MSA - Medium Sea Level Rise Scenario

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Metropolitan Statistical Area Name (Note 1)	Single Family Residences (Note 1)	Percent of Single Family Residences Exposed to Storm Surge (Note 2)	Single Family Residences Exposed to Storm Surge (Note 3)	Average Annual Storm Surge Insured Losses (Note 4)	Average Annual Storm Surge Uninsured Losses (Note 4)	Total Annual Storm Surge Insured Losses = (4) * (5)	Total Annual Storm Surge Uninsured Losses = (4) * (6)	Total Annual Storm Surge Losses = (7) + (8)	Percent of Storm Surge Losses Uninsured = (8) / (9)
Miami-Fort Lauderdale-Pompano Beach, FL	1,292,465	38.1%	491,987	$148	$438	$72,702,425	$215,446,576	$288,149,001	75%
New Orleans-Metairie, LA	371,993	96.7%	359,690	200	598	71,828,224	214,964,793	286,793,018	75%
New York-Newark-Jersey City, NY-NJ-PA	3,262,366	10.7%	348,786	160	594	55,640,594	207,057,408	262,698,002	79%
Cape Coral-Fort Myers, FL	238,495	94.8%	225,995	334	670	75,493,291	151,507,272	227,000,563	67%
Hilton Head Island-Bluffton, SC	72,147	78.8%	56,837	339	2,629	19,264,725	149,441,373	168,706,098	89%
Tampa-St. Petersburg-Clearwater, FL	849,853	34.0%	289,050	169	284	48,821,605	82,163,743	130,985,348	63%
Houston-The Woodlands-Sugar Land, TX	1,649,856	19.7%	325,231	34	348	11,109,222	113,340,195	124,449,417	91%
Naples-Marco Island, FL	95,685	98.7%	94,485	428	802	40,457,185	75,786,850	116,244,035	65%
Punta Gorda, FL	70,708	99.4%	70,308	413	720	29,036,338	50,654,107	79,690,445	64%
Charleston-North Charleston, SC	212,033	49.2%	104,216	242	504	25,170,034	52,554,982	77,725,017	68%
Houma-Thibodaux, LA	60,417	100.0%	60,417	342	893	20,680,598	53,954,652	74,635,250	72%
Jacksonville, FL	429,019	24.5%	105,005	146	550	15,354,340	57,722,069	73,076,409	79%
Virginia Beach-Norfolk-Newport News, VA-NC	523,327	63.7%	333,517	46	153	15,177,416	50,876,659	66,054,075	77%
Ocean City, NJ	75,589	87.3%	65,990	270	720	17,804,339	47,525,042	65,329,381	73%
North Port-Sarasota-Bradenton, FL	263,971	61.1%	161,282	139	258	22,391,853	41,627,904	64,019,757	65%
Boston-Cambridge-Newton, MA-NH	1,042,909	3.7%	38,297	222	1,114	8,484,175	42,666,416	51,150,591	83%
Beaumont-Port Arthur, TX	120,529	87.5%	105,425	41	424	4,328,433	44,657,069	48,985,502	91%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	156,898	26.3%	41,199	263	547	10,823,462	22,521,384	33,344,846	68%
Lafayette, LA	141,177	86.3%	121,766	101	162	12,350,384	19,767,775	32,118,159	62%
Sebastian-Vero Beach, FL	52,438	17.7%	9,307	195	2,962	1,814,158	27,563,855	29,378,012	94%
Deltona-Daytona Beach-Ormond Beach, FL	220,757	35.0%	77,320	85	252	6,594,446	19,463,547	26,057,992	75%
Jacksonville, NC	53,490	13.5%	7,199	1,104	2,508	7,947,629	18,055,536	26,003,165	69%
Lake Charles, LA	62,822	95.1%	59,721	132	278	7,854,002	16,587,823	24,441,825	68%
Palm Bay-Melbourne-Titusville, FL	190,403	25.8%	49,101	46	420	2,253,864	20,610,376	22,864,239	90%
Portland-South Portland, ME	193,001	3.1%	6,015	222	3,490	1,335,354	20,993,964	22,329,318	94%
Bridgeport-Stamford-Norwalk, CT	238,970	5.5%	13,098	297	1,307	3,896,463	17,115,216	21,011,679	81%
Salisbury, MD-DE	161,632	39.1%	63,173	136	185	8,618,012	11,656,090	20,274,103	57%
Wilmington, NC	93,347	21.7%	20,288	194	803	3,931,373	16,293,081	20,224,454	81%
Gulfport-Biloxi, MS	130,147	71.2%	92,662	34	171	3,141,877	15,862,710	19,004,587	83%
New Haven-Milford, CT	213,870	8.7%	18,697	148	853	2,761,143	15,949,430	18,710,572	85%
Port St. Lucie, FL	147,959	14.8%	21,894	226	470	4,949,942	10,298,150	15,248,093	68%
Baton Rouge, LA	241,791	37.8%	91,434	61	96	5,574,135	8,814,787	14,388,921	61%
Savannah, GA	109,497	73.7%	80,698	24	146	1,973,098	11,810,547	13,783,645	86%
Barnstable Town, MA	138,885	19.0%	26,397	40	459	1,046,991	12,104,007	13,150,998	92%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1,830,424	3.9%	72,197	41	140	2,984,847	10,109,507	13,094,354	77%
Homosassa Springs, FL	55,727	21.5%	12,006	381	701	4,575,794	8,413,449	12,989,243	65%
Daphne-Fairhope-Foley, AL	70,318	20.6%	14,504	97	740	1,404,984	10,731,875	12,136,859	88%
Mobile, AL	139,996	21.6%	30,299	59	338	1,802,121	10,256,092	12,058,212	85%
Brunswick, GA	37,880	76.3%	28,885	44	293	1,269,146	8,471,170	9,740,316	87%
Crestview-Fort Walton Beach-Destin, FL	92,891	26.9%	24,998	77	221	1,932,043	5,517,300	7,449,343	74%
Hartford-East Hartford-Middletown, CT	332,941	2.0%	6,701	160	847	1,072,402	5,674,936	6,747,338	84%
Corpus Christi, TX	121,799	31.0%	37,800	19	157	715,724	5,946,838	6,662,562	89%
Atlantic City-Hammonton, NJ	84,496	36.0%	30,399	87	120	2,638,428	3,635,082	6,273,510	58%
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,422,224	0.5%	7,299	22	753	159,747	5,498,451	5,658,198	97%
New Bern, NC	41,778	51.9%	21,689	59	174	1,270,608	3,784,012	5,054,620	75%
Norwich-New London, CT	85,235	10.3%	8,804	105	401	926,024	3,531,602	4,457,626	79%
Pensacola-Ferry Pass-Brent, FL	151,893	10.4%	15,799	90	185	1,418,732	2,926,782	4,345,514	67%
Brownsville-Harlingen, TX	98,581	41.8%	41,192	11	94	448,986	3,891,378	4,340,364	90%
Panama City, FL	55,465	31.5%	17,489	38	138	659,057	2,416,631	3,075,688	79%
Baltimore-Columbia-Towson, MD	854,053	4.1%	34,798	18	67	628,790	2,324,643	2,953,433	79%
Tallahassee, FL	100,908	8.2%	8,292	175	166	1,454,837	1,380,672	2,835,509	49%
Providence-Warwick, RI-MA	404,392	4.8%	19,404	25	87	477,164	1,685,350	2,162,514	78%
Hammond, LA	34,396	46.5%	15,998	47	80	754,155	1,274,969	2,029,124	63%
Gainesville, FL	75,798	2.2%	1,700	279	415	474,665	706,190	1,180,856	60%
Dover, DE	52,288	4.8%	2,499	75	348	188,400	869,641	1,058,041	82%
California-Lexington Park, MD	35,784	12.8%	4,598	120	54	551,172	249,565	800,737	31%
Vineland-Bridgeton, NJ	40,871	15.4%	6,296	84	29	528,593	185,158	713,751	26%
Hinesville, GA	19,678	23.4%	4,595	2	144	9,169	662,868	672,037	99%
Orlando-Kissimmee-Sanford, FL	649,296	0.1%	500	222	11	111,198	5,465	116,663	5%
Bangor, ME	50,205	0.4%	200	0	459	0	91,820	91,820	100%
Richmond, VA	390,291	0.5%	2,000	6	27	12,167	54,646	66,812	82%
Greenville, NC	44,156	0.9%	400	8	72	3,116	28,949	32,065	90%
Kingston, NY	61,429	0.2%	100	214	13	21,429	1,315	22,744	6%
Total All MSAs	74,520,514	6.0%	4,507,928	$148	$452	$669,104,628	$2,037,741,745	$2,706,846,373	75%
Total Outside MSAs	16,212,126	1.7%	271,117	217	432	58,700,794	117,183,666	175,884,460	67%
Total	90,732,640	5.3%	4,779,045	152	451	727,805,422	2,154,925,411	2,882,730,833	75%

Notes:
1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Any given location is deemed to have storm surge exposure if its combined inland flood and storm surge ground up loss is greater than its inland flood loss alone.
3. Column (4) = Column (2) * Column (3).
4. Loss data is ground up storm surge losses sourced KatRisk catastrophe model runs on a subset of Milliman market basket locations. Modeling runs were set to a medium sea level rise scenario.
5. Insured and Uninsured losses are based on estimates of NFIP take-up rates and coverages.

Exhibit 12: Storm Surge Losses by MSA - High Sea Level Rise Scenario

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Metropolitan Statistical Area Name (Note 1)	Single Family Residences (Note 1)	Percent of Single Family Residences Exposed to Storm Surge (Note 2)	Single Family Residences Exposed to Storm Surge (Note 3)	Average Annual Storm Surge Insured Losses (Note 4)	Average Annual Storm Surge Uninsured Losses (Note 4)	Total Annual Storm Surge Insured Losses = (4) * (5)	Total Annual Storm Surge Uninsured Losses = (4) * (6)	Total Annual Storm Surge Losses = (7) + (8)	Percent of Storm Surge Losses Uninsured = (8) / (9)
New York-Newark-Jersey City, NY-NJ-PA	3,262,366	11.2%	364,585	$246	$901	$89,611,876	$328,321,022	$417,932,899	79%
Miami-Fort Lauderdale-Pompano Beach, FL	1,292,465	39.8%	513,786	189	571	97,226,532	293,214,517	390,441,049	75%
New Orleans-Metairie, LA	371,993	96.8%	360,190	221	681	79,649,017	245,125,855	324,774,871	75%
Cape Coral-Fort Myers, FL	238,495	95.3%	227,395	420	859	95,507,309	195,442,677	290,949,985	67%
Hilton Head Island-Bluffton, SC	72,147	81.7%	58,938	427	3,279	25,181,584	193,249,254	218,430,838	88%
Tampa-St. Petersburg-Clearwater, FL	849,853	34.8%	295,449	222	368	65,648,641	108,753,552	174,402,192	62%
Naples-Marco Island, FL	95,685	98.9%	94,585	546	1,059	51,602,207	100,171,782	151,773,988	66%
Houston-The Woodlands-Sugar Land, TX	1,649,856	20.0%	329,231	42	417	13,922,089	137,221,066	151,143,155	91%
Charleston-North Charleston, SC	212,033	50.0%	106,017	343	751	36,345,891	79,571,570	115,917,461	69%
Ocean City, NJ	75,589	89.8%	67,890	453	1,235	30,787,988	83,853,367	114,641,355	73%
Jacksonville, FL	429,019	26.0%	111,505	207	768	23,096,487	85,584,729	108,681,216	79%
Virginia Beach-Norfolk-Newport News, VA-NC	523,327	65.5%	342,518	71	232	24,426,584	79,325,266	103,751,850	76%
Punta Gorda, FL	70,708	99.9%	70,608	522	909	36,883,999	64,153,239	101,037,238	63%
Houma-Thibodaux, LA	60,417	100.0%	60,417	451	1,187	27,250,881	71,739,610	98,990,491	72%
North Port-Sarasota-Bradenton, FL	263,971	63.2%	166,882	183	337	30,522,010	56,296,798	86,818,808	65%
Boston-Cambridge-Newton, MA-NH	1,042,909	4.0%	41,596	282	1,531	11,737,707	63,692,170	75,429,877	84%
Beaumont-Port Arthur, TX	120,529	87.6%	105,625	48	496	5,040,445	52,342,089	57,382,534	91%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	156,898	28.1%	44,099	331	704	14,589,288	31,031,278	45,620,566	68%
Sebastian-Vero Beach, FL	52,438	18.9%	9,907	244	4,055	2,413,047	40,173,651	42,586,698	94%
Lafayette, LA	141,177	87.2%	123,167	121	195	14,845,505	24,029,604	38,875,109	62%
Salisbury, MD-DE	161,632	40.5%	65,472	243	336	15,936,859	22,019,817	37,956,676	58%
Deltona-Daytona Beach-Ormond Beach, FL	220,757	35.4%	78,220	120	349	9,387,808	27,288,947	36,676,755	74%
Jacksonville, NC	53,490	14.0%	7,499	1,291	3,136	9,683,576	23,512,590	33,196,166	71%
Portland-South Portland, ME	193,001	3.4%	6,648	259	4,514	1,724,381	30,009,777	31,734,158	95%
Bridgeport-Stamford-Norwalk, CT	238,970	5.6%	13,298	415	1,958	5,512,782	26,038,707	31,551,489	83%
Palm Bay-Melbourne-Titusville, FL	190,403	26.3%	50,101	63	547	3,164,806	27,381,662	30,546,468	90%
Lake Charles, LA	62,822	95.1%	59,721	160	340	9,572,733	20,312,648	29,885,382	68%
Wilmington, NC	93,347	23.7%	22,087	243	1,017	5,375,201	22,472,474	27,847,675	81%
New Haven-Milford, CT	213,870	9.1%	19,497	201	1,162	3,920,461	22,655,347	26,575,808	85%
Gulfport-Biloxi, MS	130,147	71.3%	92,762	43	215	3,959,114	19,954,365	23,913,479	83%
Port St. Lucie, FL	147,959	17.5%	25,893	256	575	6,624,452	14,891,632	21,516,085	69%
Savannah, GA	109,497	76.2%	83,398	35	210	2,942,412	17,510,302	20,452,715	86%
Barnstable Town, MA	138,885	20.0%	27,797	60	648	1,659,821	18,026,162	19,685,983	92%
Baton Rouge, LA	241,791	38.6%	93,335	77	119	7,185,651	11,084,038	18,269,689	61%
Daphne-Fairhope-Foley, AL	70,318	20.8%	14,604	145	989	2,112,344	14,448,919	16,561,262	87%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1,830,424	4.3%	77,997	47	163	3,627,771	12,697,447	16,325,218	78%
Homosassa Springs, FL	55,727	21.5%	12,006	477	880	5,725,726	10,565,862	16,291,588	65%
Mobile, AL	139,996	23.0%	32,199	69	400	2,219,603	12,867,893	15,087,496	85%
Brunswick, GA	37,880	77.3%	29,285	65	439	1,915,828	12,863,185	14,779,014	87%
Atlantic City-Hammonton, NJ	84,496	36.7%	30,999	176	231	5,460,689	7,170,061	12,630,750	57%
Crestview-Fort Walton Beach-Destin, FL	92,891	28.6%	26,597	105	300	2,793,703	7,976,690	10,770,393	74%
Hartford-East Hartford-Middletown, CT	332,941	2.0%	6,801	220	1,240	1,498,861	8,433,652	9,932,512	85%
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,422,224	0.5%	7,699	32	1,209	245,810	9,310,125	9,555,934	97%
Corpus Christi, TX	121,799	32.3%	39,400	27	213	1,061,635	8,378,563	9,440,198	89%
New Bern, NC	41,778	55.5%	23,188	86	251	1,987,483	5,825,496	7,812,980	75%
Norwich-New London, CT	85,235	11.2%	9,504	147	589	1,398,681	5,593,205	6,991,886	80%
Pensacola-Ferry Pass-Brent, FL	151,893	11.1%	16,899	124	233	2,088,794	3,944,828	6,033,622	65%
Baltimore-Columbia-Towson, MD	854,053	4.5%	38,398	29	113	1,126,757	4,334,489	5,461,246	79%
Brownsville-Harlingen, TX	98,581	43.3%	42,692	13	110	574,315	4,686,010	5,260,325	89%
Panama City, FL	55,465	35.5%	19,688	50	187	991,476	3,681,251	4,672,727	79%
Providence-Warwick, RI-MA	404,392	5.2%	21,205	38	127	811,115	2,699,086	3,510,201	77%
Tallahassee, FL	100,908	8.4%	8,492	204	193	1,736,592	1,640,948	3,377,540	49%
Hammond, LA	34,396	48.0%	16,498	53	90	868,259	1,489,468	2,357,727	63%
Dover, DE	52,288	5.2%	2,699	105	473	283,603	1,277,009	1,560,612	82%
California-Lexington Park, MD	35,784	14.0%	4,998	219	80	1,096,129	397,474	1,493,603	27%
Gainesville, FL	75,798	2.2%	1,700	345	517	586,833	878,405	1,465,237	60%
Vineland-Bridgeton, NJ	40,871	15.6%	6,395	137	39	874,974	247,988	1,122,962	22%
Hinesville, GA	19,678	23.9%	4,695	3	193	13,665	908,118	921,782	99%
Orlando-Kissimmee-Sanford, FL	649,296	0.1%	600	322	13	193,265	8,051	201,316	4%
Richmond, VA	390,291	0.6%	2,200	7	36	15,641	78,761	94,402	83%
Bangor, ME	50,205	0.4%	200	0	460	0	91,949	91,949	100%
Kingston, NY	61,429	0.3%	200	158	44	31,639	8,791	40,430	22%
Greenville, NC	44,156	1.4%	599	5	49	3,199	29,395	32,594	90%
Total All MSAs	74,520,514	6.2%	4,638,556	$195	$599	$904,283,533	$2,778,984,685	$3,683,268,218	75%
Total Outside MSAs	16,212,126	1.7%	278,918	304	609	84,708,898	169,861,279	254,570,177	67%
Total	90,732,640	5.4%	4,917,473	201	600	988,992,430	2,948,845,964	3,937,838,395	75%

Notes:
1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Any given location is deemed to have storm surge exposure if its combined inland flood and storm surge ground up loss is greater than its inland flood loss alone.
3. Column (4) = Column (2) * Column (3).
4. Loss data is ground up storm surge losses sourced KatRisk catastrophe model runs on a subset of Milliman market basket locations. Modeling runs were set to a high sea level rise scenario.
5. Insured and Uninsured losses are based on estimates of NFIP take-up rates and coverages.

Exhibit 13: Ratio of Average Annual Loss to Census Block Group Median Household Income – Averaged by MSA

(1)	(2)	(3)	(4)	(5)
Metropolitan Statistical Area Title (Note 1)	Median Household Income (Notes, 1, 3)	Ratio of AAL to Median Census Block Group Household Income (Note 2)		
		Current Sea Levels	Medium Sea Level Rise	High Sea Level Rise
Hilton Head Island-Bluffton, SC	$66,216	2.13%	2.52%	3.29%
Houma-Thibodaux, LA	53,429	1.87%	2.50%	3.32%
Punta Gorda, FL	50,828	1.89%	2.21%	2.78%
Naples-Marco Island, FL	71,931	1.37%	1.65%	2.16%
Cape Coral-Fort Myers, FL	57,439	1.24%	1.48%	1.88%
New Orleans-Metairie, LA	54,743	1.25%	1.39%	1.57%
Ocean City, NJ	67,360	0.88%	1.26%	2.21%
Beaumont-Port Arthur, TX	52,698	0.75%	0.86%	1.00%
Jacksonville, NC	48,976	0.73%	0.83%	1.04%
Lake Charles, LA	51,489	0.66%	0.80%	0.98%
Homosassa Springs, FL	40,480	0.63%	0.71%	0.86%
Sebastian-Vero Beach, FL	59,061	0.46%	0.54%	0.74%
Lafayette, LA	51,303	0.38%	0.48%	0.58%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	51,418	0.37%	0.42%	0.54%
Wilmington, NC	58,174	0.36%	0.40%	0.50%
Charleston-North Charleston, SC	63,837	0.31%	0.40%	0.59%
North Port-Sarasota-Bradenton, FL	59,862	0.34%	0.38%	0.50%
Brunswick, GA	50,934	0.28%	0.37%	0.56%
Gulfport-Biloxi, MS	48,693	0.31%	0.35%	0.44%
Daphne-Fairhope-Foley, AL	56,466	0.31%	0.35%	0.44%
Miami-Fort Lauderdale-Pompano Beach, FL	64,364	0.29%	0.34%	0.44%
Tampa-St. Petersburg-Clearwater, FL	57,775	0.26%	0.29%	0.37%
Deltona-Daytona Beach-Ormond Beach, FL	48,856	0.24%	0.27%	0.36%
Port St. Lucie, FL	54,792	0.24%	0.26%	0.31%
Jacksonville, FL	59,253	0.21%	0.26%	0.36%
New Bern, NC	49,003	0.20%	0.25%	0.38%
Palm Bay-Melbourne-Titusville, FL	56,000	0.22%	0.25%	0.30%
Mobile, AL	45,242	0.20%	0.22%	0.26%
Barnstable Town, MA	72,436	0.17%	0.20%	0.28%
Portland-South Portland, ME	71,271	0.17%	0.19%	0.25%
Houston-The Woodlands-Sugar Land, TX	70,164	0.17%	0.18%	0.20%
Brownsville-Harlingen, TX	37,733	0.15%	0.17%	0.19%
Hammond, LA	46,144	0.16%	0.17%	0.18%
Baton Rouge, LA	57,759	0.15%	0.17%	0.20%
Savannah, GA	54,330	0.13%	0.16%	0.24%
Salisbury, MD-DE	62,635	0.12%	0.16%	0.28%
Virginia Beach-Norfolk-Newport News, VA-NC	67,805	0.13%	0.16%	0.24%
Gainesville, FL	50,330	0.15%	0.16%	0.17%
New Haven-Milford, CT	73,904	0.14%	0.15%	0.20%
Crestview-Fort Walton Beach-Destin, FL	62,098	0.13%	0.15%	0.20%
New York-Newark-Jersey City, NY-NJ-PA	88,044	0.13%	0.14%	0.20%
Kingston, NY	66,448	0.14%	0.14%	0.15%
Panama City, FL	53,184	0.12%	0.14%	0.19%
Corpus Christi, TX	56,531	0.11%	0.14%	0.18%
Bridgeport-Stamford-Norwalk, CT	113,697	0.11%	0.12%	0.15%
Atlantic City-Hammonton, NJ	63,478	0.08%	0.12%	0.23%
Norwich-New London, CT	77,196	0.10%	0.12%	0.15%
Pensacola-Ferry Pass-Brent, FL	56,740	0.11%	0.11%	0.13%
Boston-Cambridge-Newton, MA-NH	95,487	0.10%	0.11%	0.14%
Tallahassee, FL	54,817	0.10%	0.11%	0.12%
Greenville, NC	46,838	0.09%	0.09%	0.09%
Hinesville, GA	49,396	0.07%	0.08%	0.11%
Dover, DE	58,645	0.07%	0.08%	0.10%
Orlando-Kissimmee-Sanford, FL	60,167	0.07%	0.07%	0.07%
California-Lexington Park, MD	89,942	0.06%	0.07%	0.09%
Hartford-East Hartford-Middletown, CT	82,828	0.06%	0.06%	0.07%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	74,769	0.06%	0.06%	0.06%
Vineland-Bridgeton, NJ	56,640	0.04%	0.05%	0.07%
Providence-Warwick, RI-MA	68,499	0.04%	0.04%	0.04%
Richmond, VA	69,114	0.04%	0.04%	0.04%
Washington-Arlington-Alexandria, DC-VA-MD-WV	111,529	0.03%	0.03%	0.03%
Bangor, ME	50,450	0.03%	0.03%	0.03%
Baltimore-Columbia-Towson, MD	82,762	0.02%	0.02%	0.03%

Notes:
1. Data is sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Total Loss data is ground up inland flood and storm surge losses sourced Katrisk catastrophe model runs on a subset of Milliman market basket locations.
3. MSA level median household income was found by taking the average of median household income at the census block group level for all census block groups within a given MSA.

Exhibit 14: Change in 500 Year Return Period Flood Losses for Sea Level Rise Scenarios Compared to Current Sea Levels

(1)	(2)	(3)	(4)	(5)	(6)	(7)
		500 Year Return Period Event 500 Year Return Period Event Total Losses			500 Year Return Period Event Percent Total Loss Increase	
Metropolitan Statistical Area Name (Note 1)	Single Family Residences (Note 1)	Current Sea Level (Note 2)	Medium Sea Level Rise (Note 2)	High Sea Level Rise (Note 2)	Medium Sea Level Rise vs. Current Sea Level = ((4) - (3)) / (3)	High Sea Level Rise vs. Current Sea Level = ((5) - (3)) / (3)
Atlantic City-Hammonton, NJ	84,496	$362,430,776	$517,973,620	$1,022,388,888	42.9%	182.1%
Ocean City, NJ	75,589	2,640,784,247	3,434,388,722	5,161,489,799	30.1%	95.5%
Salisbury, MD-DE	161,632	971,553,505	1,256,196,402	1,905,236,917	29.3%	96.1%
Savannah, GA	109,497	1,042,258,575	1,342,122,747	1,921,665,551	28.8%	84.4%
Brunswick, GA	37,880	646,274,261	829,589,873	1,191,184,136	28.4%	84.3%
Charleston-North Charleston, SC	212,033	4,185,234,641	5,133,704,055	7,019,067,066	22.7%	67.7%
New Bern, NC	41,778	331,955,342	402,342,741	558,266,630	21.2%	68.2%
Virginia Beach-Norfolk-Newport News, VA-NC	523,327	2,646,227,542	3,199,814,645	4,468,560,601	20.9%	68.9%
Lake Charles, LA	62,822	2,131,971,128	2,575,623,077	3,048,489,169	20.8%	43.0%
Lafayette, LA	141,177	2,039,553,711	2,435,222,403	2,836,245,454	19.4%	39.1%
Corpus Christi, TX	121,799	645,844,971	769,941,306	906,521,476	19.2%	40.4%
Hinesville, GA	19,678	86,598,049	102,660,873	132,150,416	18.5%	52.6%
Houma-Thibodaux, LA	60,417	3,427,551,097	4,054,513,220	4,694,094,855	18.3%	37.0%
Barnstable Town, MA	138,885	645,013,230	747,408,192	1,046,199,745	15.9%	62.2%
Norwich-New London, CT	85,235	413,603,226	474,407,657	658,782,871	14.7%	59.3%
Naples-Marco Island, FL	95,685	8,418,978,839	9,652,428,169	11,700,316,167	14.7%	39.0%
Miami-Fort Lauderdale-Pompano Beach, FL	1,292,465	20,340,408,122	23,113,537,953	28,106,226,804	13.6%	38.2%
Jacksonville, FL	429,019	3,804,710,357	4,315,520,562	5,303,511,334	13.4%	39.4%
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	156,898	2,268,212,275	2,569,841,942	3,245,084,009	13.3%	43.1%
Gulfport-Biloxi, MS	130,147	1,645,325,078	1,844,341,416	2,196,462,593	12.1%	33.5%
Vineland-Bridgeton, NJ	40,871	56,962,003	63,763,884	77,758,669	11.9%	36.5%
Crestview-Fort Walton Beach-Destin, FL	92,891	622,399,371	693,838,989	881,080,867	11.5%	41.6%
Tampa-St. Petersburg-Clearwater, FL	849,853	10,552,205,581	11,726,579,381	14,170,266,275	11.1%	34.3%
Deltona-Daytona Beach-Ormond Beach, FL	220,757	2,128,314,643	2,363,626,803	2,846,803,715	11.1%	33.8%
Beaumont-Port Arthur, TX	120,529	4,136,931,309	4,591,625,309	5,107,839,059	11.0%	23.5%
North Port-Sarasota-Bradenton, FL	263,971	4,892,636,151	5,425,892,573	6,616,914,002	10.9%	35.2%
Cape Coral-Fort Myers, FL	238,495	17,578,399,236	19,488,597,567	22,350,598,971	10.9%	27.1%
Panama City, FL	55,465	350,669,368	388,420,836	493,870,890	10.8%	40.8%
Hilton Head Island-Bluffton, SC	72,147	6,351,094,038	7,034,450,781	8,177,827,700	10.8%	28.8%
Sebastian-Vero Beach, FL	52,438	1,466,731,259	1,624,349,559	1,899,142,929	10.7%	29.5%
Daphne-Fairhope-Foley, AL	70,318	724,944,865	798,099,880	968,551,673	10.1%	33.6%
Wilmington, NC	93,347	1,461,575,060	1,604,176,624	1,942,715,791	9.8%	32.9%
New Haven-Milford, CT	213,870	1,463,463,262	1,606,085,966	1,921,764,452	9.7%	31.3%
Palm Bay-Melbourne-Titusville, FL	190,403	2,073,766,310	2,263,058,733	2,667,315,832	9.1%	28.6%
Portland-South Portland, ME	193,001	1,381,335,025	1,505,869,025	1,851,182,778	9.0%	34.0%
Baton Rouge, LA	241,791	1,608,658,881	1,749,674,462	1,969,420,766	8.8%	22.4%
Punta Gorda, FL	70,708	6,560,020,807	7,126,167,679	8,008,198,581	8.6%	22.1%
New York-Newark-Jersey City, NY-NJ-PA	3,262,366	12,814,631,896	13,790,870,482	16,466,194,589	7.6%	28.5%
Mobile, AL	139,996	706,914,457	760,477,719	852,008,287	7.6%	20.5%
Boston-Cambridge-Newton, MA-NH	1,042,909	3,175,352,710	3,406,121,712	4,134,800,792	7.3%	30.2%
Homosassa Springs, FL	55,727	1,021,531,705	1,078,550,868	1,177,613,475	5.6%	15.3%
California-Lexington Park, MD	35,784	152,341,838	160,360,516	183,087,226	5.3%	20.2%
Port St. Lucie, FL	147,959	1,507,227,983	1,586,452,485	1,751,038,904	5.3%	16.2%
New Orleans-Metairie, LA	371,993	13,737,164,558	14,454,744,384	15,314,118,953	5.2%	11.5%
Bridgeport-Stamford-Norwalk, CT	238,970	1,952,259,033	2,054,111,847	2,346,150,126	5.2%	20.2%
Jacksonville, NC	53,490	1,026,480,191	1,079,084,217	1,162,936,642	5.1%	13.3%
Houston-The Woodlands-Sugar Land, TX	1,649,856	12,303,369,318	12,901,889,116	13,843,318,052	4.9%	12.5%
Hartford-East Hartford-Middletown, CT	332,941	934,100,657	975,360,784	1,085,135,448	4.4%	16.2%
Pensacola-Ferry Pass-Brent, FL	151,893	743,214,785	773,403,621	855,264,199	4.1%	15.1%
Brownsville-Harlingen, TX	98,581	489,992,331	509,879,804	534,085,364	4.1%	9.0%
Tallahassee, FL	100,908	437,015,592	452,710,654	481,798,780	3.6%	10.2%
Hammond, LA	34,396	243,081,634	248,949,976	259,753,682	2.4%	6.9%
Baltimore-Columbia-Towson, MD	854,053	1,156,427,858	1,175,000,239	1,227,743,826	1.6%	6.2%
Providence-Warwick, RI-MA	404,392	786,868,304	799,017,652	852,565,894	1.5%	8.3%
Dover, DE	52,288	118,657,037	119,729,080	121,670,348	0.9%	2.5%
Gainesville, FL	75,798	357,238,027	358,516,564	359,952,367	0.4%	0.8%
Washington-Arlington-Alexandria, DC-VA-MD-WV	1,422,224	3,391,657,515	3,394,115,057	3,398,066,680	0.1%	0.2%
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1,830,424	4,340,819,317	4,342,270,803	4,351,138,771	0.0%	0.2%
Richmond, VA	390,291	781,569,090	781,640,458	782,122,857	0.0%	0.1%
Orlando-Kissimmee-Sanford, FL	649,296	2,808,656,721	2,808,865,318	2,809,292,195	0.0%	0.0%
Kingston, NY	61,429	305,322,894	305,336,995	305,377,933	0.0%	0.0%
Greenville, NC	44,156	218,971,172	218,980,565	218,994,557	0.0%	0.0%
Bangor, ME	50,205	51,483,429	51,483,429	51,483,429	0.0%	0.0%

Notes:
1. MSAs and residential populations are sourced from the 2017 five year American Community Survey, provided by the United States Census Bureau.
2. Total Losses in Columns (3), (4) and (5) are ground up inland flood and storm surge losses sourced from Katrisk model runs simulating an event with a 500 year return period under standard, medium and high sea level rise scenarios, respectively.

5.3 OVERVIEW OF MILLIMAN M-PIRE: MORTGAGE ANALYTIC METHODOLOGY

Milliman's Mortgage Platform for Investments and Reinsurance (M-PIRe) is an integrated platform hosted on Microsoft's Azure cloud and was built by Milliman specifically to evaluate mortgage credit risk transfer securities and reinsurance exposures. M-PIRe is used by GSE CRT market participants to perform key functions when evaluating specific deals and holistically managing their portfolio.

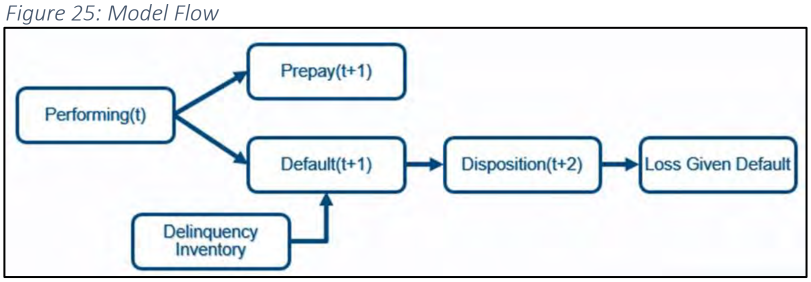
M-PIRe's robust modeling framework and customization flexibility made it an appropriate tool to use for performing the analyses in this paper. Specific M-PIRe features leveraged for this analysis include the Loan level Mortgage Performance Model, Loan Level Economic Scenario Engine, and CRT Deal Cash Flow Waterfall Library.

Loan level Mortgage Performance Model

M-PIRe's Loan Level Mortgage Performance Model combines loan-level data, loan-level econometric models, and economic scenario forecasts to produce deterministic cash-flow estimates for each loan (and ultimately each CRT exposure). Specifically, M-PIRe estimates quarterly conditional prepayment, default, and loss severity (also referred to as "loss given default") rates for each active loan included in the reference pools underlying the transactions for all periods beyond the evaluation date. These estimates are generated using various economic scenarios and our econometric mortgage performance model. The econometric mortgage performance model was developed using publicly available Fannie Mae and Freddie Mac data and translates the historical mortgage performance data and economic data into future estimates. After generating the mortgage collateral performance estimates, M-PIRe passes the aggregated estimates to the cash-flow model to generate CRT cash flows under the various deterministic economic scenarios.

The model estimates the performance of loans through a binomial logistic regression framework where the risk of prepayment and default are competing risks. The figure below provides a visual of the main components of the model.

Figure 25: Model Flow



The first stage of the framework, the Performing Loan Model, estimates the probability of a loan transitioning from performing status to either prepayment or default—where default is defined as 180 days or more delinquent. The second stage of the framework, the Non-Performing Loan Model, estimates the probability of a loan transitioning from default to disposition (i.e., title transferred to investor and sold through the foreclosure process or real estate owned inventory). The transition probabilities generate dynamic estimates that vary according to a loan's underwriting characteristics, age, and economic influences. For loans that are estimated to result in a property disposition, the third stage of the framework is a Loss Severity Model to estimate the ultimate losses that will flow through the CRT structure as a result of the loan default.

Performing Loan Model

The Performing Loan Model estimates the quarterly conditional probability of a loan transitioning from performing status to either prepayment or default (defined as 180 days or more delinquent). This model was parameterized using a combination of the Fannie Mae single-family loan performance data and the Freddie Mac single-family loan level dataset. Both datasets contain mortgage loans that are fixed rate and fully amortizing. The dataset contains performance results for more than 60 million mortgages acquired by the GSEs. Once expanded to the quarterly panel dataset, the final estimation dataset contained more than 375 million quarterly observations of loan performance.

Table 10: Performing Loan Model Variable Overview - Dynamic Economic Factors

Variable	Value	Prepayment	Default
Cumulative Home Price Appreciation	High HPA Low HPA	Increase Decrease	Decrease Increase
One-Year Change in HPA	High HPA Low HPA	Increase Decrease	Decrease Increase
Spread relative to 10-Year Interest Rate	High Spread Low Spread	Increase Decrease	N/A
Unemployment Rate	High Rate Low Rate	N/A	Increase Decrease

Below is a high-level description of the predictor variables in the model and their impact on prepayment and default probabilities. Note that the variables are partitioned into two tables to illustrate the static loan characteristic that drive mortgage performance versus the dynamic economic factors that drive mortgage performance.

Section 4 describes the analysis methodology in this paper where the dynamic economic factors are altered to correspond to specific flood events. This is the main channel (HPA variables in Performing, Non-Performing, and Gross Severity models) for translating the flood events into M-PIRe and producing estimates of mortgage performance (and ultimately CRT deal performance) under the events.

Table 11: Performing Loan Model Variable Overview – Static Loan Characteristics

Variable	Value	Prepayment	Default
Loan-to-Value Ratio	High Ratio Low Ratio	Decrease Increase	Increase Decrease
Credit Score	High Score Low Score	Increase Decrease	Decrease Increase
Debt to Income Ratio	High Ratio Low Ratio	N/A	Increase Decrease
Occupancy Status	Owner Investor Second	Reference Decrease Decrease	Reference Increase Decrease
Property Type	SFR Condo Co-op Manufactured PUD Unknown	Reference Decrease Decrease Decrease Decrease Decrease	Reference Decrease Decrease Increase Decrease Decrease
Loan Purpose	Purchase Cash out Rate/term Unknown	Reference Decrease Decrease Increase	Reference Increase Increase Increase
Term	360 LT360 GT360	Reference Increase Decrease	Reference Decrease Increase
Original Loan Amount	High Amount Low Amount	Reference Decrease	Reference Increase
Number of Borrowers	1 Borrower 2+ Borrowers Unknown	N/A	Increase Reference Increase
Number of Units	1	N/A	Reference

	2 3 4+		Increase Increase Decrease
First Time Home Buyer	Yes No Unknown	Decrease Reference Decrease	Decrease Reference Decrease
Spread at Origination	High Spread Low Spread	N/A	Increase Decrease

Non-Performing Loan Model

The Non-Performing Loan Model estimates the lifetime probability of a loan transitioning from the current delinquency status to 180-day delinquency status (e.g., 30-day to 180-day), and subsequently foreclosure/disposition.

The model estimates the probabilities of each status transition to 180 days delinquency using linear regression. The linear regression has a single explanatory variable: borrower equity at the time of delinquency. Equity is measured as initial equity (one minus combined loan-to-value ratio) adjusted for cumulative home price appreciation. As stated above, HPA is the mechanism for translating the flood events into M-PIRe and producing performance (and ultimately CRT deal performance) under the event

This roll-rate/transition methodology is a key component used in Section 4 to provide estimates of loans 60+ days delinquent as a result of the flood event.

Gross Severity Model

The gross severity, or loss given default, model estimates the ground-up loss for a default as a percent of original loan balance. Note that this model estimates the indicated severity of loss prior to the estimation of recoveries on any MI policies that may be in place. M-PIRe has a separate component to estimate and net out MI recoveries. The gross severity model is comprised of three components:

1. Unpaid principal balance at termination
2. Delinquent interest plus disposition expenses
3. Net sale proceeds

Figure 26: Loan Level Performance

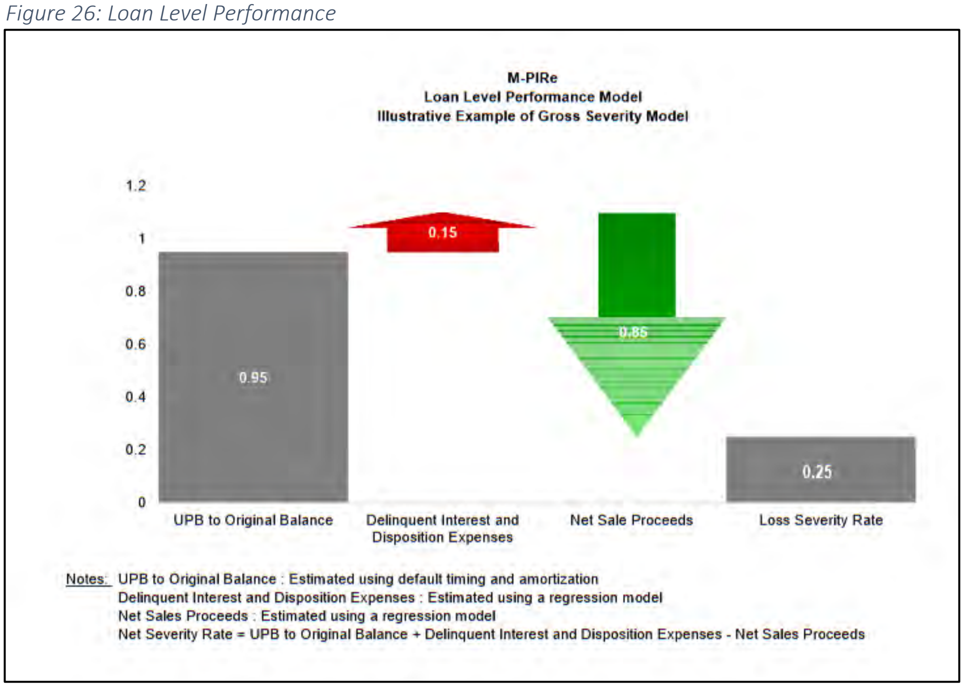
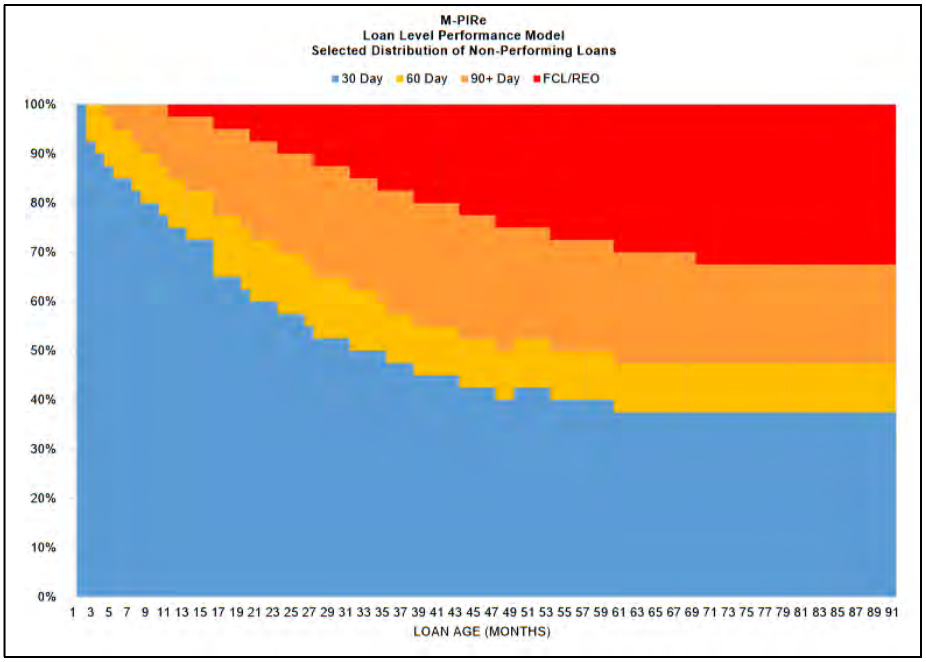


Figure 26 provides a visual of the model components. In the illustrative example, the severity rate estimates of 25% of the original loan balance is equal to the UPB at delinquency (95%) plus delinquent interest and disposition expense (15%) minus net sale proceeds (85%). HPA is a key predictor variable when estimating the net sale proceeds.

Loan Level Economic Scenario Engine

Figure 27: Loan Level Model Diagram

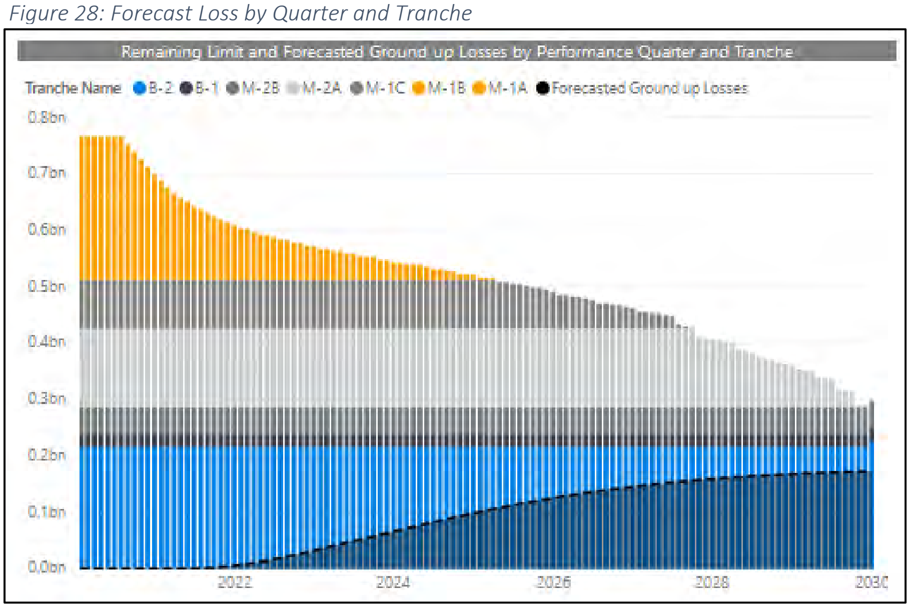


M-PIRe includes access to Moody's Analytics scenarios as well as custom user-defined stress scenarios. M-PIRe has the ability to map economic scenarios at the loan level to specific loans so as to reflect differences in economics at the granular geographic level. This feature is key to the analysis described in Section 4 when mapping property value shocks as a result of flood events to specific homes included in the modeled CRT transactions.

CRT Deal Cash Flow Waterfall Library

M-PIRe includes a complete library of the cash-flow waterfalls for all credit risk transfer deals from Freddie Mac and Fannie Mae completed to date. The waterfalls include details on the capital structure, including deal triggers, the ability to turn on or off optional call features, and historical collateral performance and bond/insurance cash flows.

Figure 28: Forecast Loss by Quarter and Tranche



These waterfalls are crucial to turning the projected losses of the underlying collateral into cash flows to/from CRT investors/reinsurers. Figure 28 provides a visual of the structure pay-down on a hypothetical CRT deal structure.

Together, these components of M-PIRe allowed us to run new flood event scenarios through the M-PIRe platform at the loan level to derive estimates of loan and deal impacts as a result of the event.

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Limitations

Data Reliances

In performing this analysis, we relied upon information obtained from other sources. We have not audited or verified this data and information. If the underlying data or information is inaccurate or incomplete, the results of our analysis may likewise be inaccurate or incomplete. In that event, the results of our analysis may not be suitable for the intended purpose.

We performed a limited review of the data used directly in our analysis for reasonableness and consistency. We did not find material defects in the data. If there are material defects in the data, it is possible that they would be uncovered by a detailed, systematic review and comparison of the data to search for data values that are questionable or relationships that are materially inconsistent. Such a detailed review was beyond the scope of our assignment.

Model Reliances

Our analysis is based on the KatRisk catastrophe model. We have reviewed the model output for reasonableness and consistency. However, no catastrophe model is entirely accurate. To the extent that the model is biased, the resulting analysis may be biased.