

Stress testing insurance market stability under climate risk

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Abstract

Climate change, urban development, and evolving insurance markets threaten the stability of disaster risk financing. Homeowners insurance is embedded in a layered network of reinsurers, capital markets, and public backstops that can be overwhelmed by extreme events. We develop a probabilistic risk propagation model to stress test insurance systems and parameterize it for tropical cyclone wind and flood risk in Florida's residential insurance market. The mean residual financing requirement rises disproportionately with economic losses, from 4.9% of mean losses for seasons between the 10- and 25-year loss thresholds to 18.4% for seasons above the 100-year threshold. The probability that this financing need exceeds 1% of Florida's gross domestic product is 3.4% under present-day conditions and rises to 8.7% by mid-century under Shared Socioeconomic Pathway 2–4.5 (SSP2–4.5). Residual deficits from private insurer insolvencies make up the largest share of the requirement, followed by Citizens, Florida's residual insurer, and the National Flood Insurance Program. We also assess stylized changes in market structure, insurance coverage, and physical losses. With the insurance market held fixed, returning mean financing needs to their present-day level requires roughly halving economic losses relative to unmitigated mid-century conditions. Together, these analyses provide a unified quantitative framework for assessing how climate change, insurance coverage, market structure, and physical damage reduction shape financing needs and systemic risk.

Key Points

- Linking hurricane losses to the insurance market components designed to absorb and distribute them reveals who bears disaster costs
- Residual financing needs rise disproportionately with hurricane losses, revealing nonlinear amplification of financial stress
- We assess how climate change, coverage, market structure, and physical damage reduction affect financing needs in one quantitative framework

Plain Language Summary

Hurricanes damage property, but the costs of recovery depend on who is insured and how insurers and public programs finance claims. We develop a model to test how insurance systems cope with extreme events and tailor it to hurricane risk in Florida. The model tracks uninsured losses, insurer failures, and residual financing needs, meaning the funds still required after available resources are used. Using historical storms and thousands of simulated hurricane seasons, we examine how climate change and hypothetical changes in insurance coverage, the organization of insurance markets, and building damage affect financing gaps within the same model. As hurricane seasons become more damaging, residual financing needs grow faster than the damage itself, amplifying financial strain on the insurance system. Climate change amplifies these financing gaps, making the response of the insurance system increasingly consequential. Wider insurance coverage protects against uninsured losses but can also shift greater financing demands onto public programs. In contrast, reducing physical damage lowers both losses and financing needs. Insurance stability, household protection, and damage prevention therefore need to be assessed together. While we focus here on hurricane risk in Florida, we emphasize that the framework can be adapted to other regions by representing their hazards, insurance markets, and financing arrangements.

1 Introduction

The 2017 Atlantic hurricane season, including Hurricanes Harvey, Irma, and Maria, caused more than USD 260 billion in economic losses (unadjusted for inflation) ([NOAA National Centers for Environmental Information, 2025](#)), making 2017 the costliest year on record for insured catastrophe losses at the time ([Swiss Re Institute, 2018](#)). The increasing likelihood of many weather and climate extremes ([Seneviratne et al., 2021](#)) and of compound events ([Zscheischler et al., 2018](#)) erodes the stationarity that underpins traditional disaster risk assessment and pricing ([Kousky, 2019](#)).

Disaster insurance transfers losses from households to insurers and state-backed providers, enabling post-disaster repairs, supporting mortgage markets, and accelerating economic recovery after extreme events ([Gallagher & Hartley, 2017](#); [Kousky, 2019](#)). Primary insurers absorb losses up to their capital and reinsurance protection, after which risks propagate to reinsurers, catastrophe bond investors, and public backstops such as state insurance programs or federal institutions. Under moderate shocks, this structure spreads risk efficiently; under extreme or clustered events, however, contractual limits, capital constraints, and regulatory thresholds can bind, causing losses to cascade across institutions rather than being smoothly absorbed ([Kunreuther & Useem, 2010](#); [Jarzabkowski et al., 2023](#); [Kousky et al., 2024](#)). A single costly year is within the volatility that capital and reinsurance are designed to absorb. Less certain is whether intensifying hazards and growing

insurance market strain push an increasing share of losses beyond the system’s capacity and onto households and the public (Cummins & Weiss, 2014; Jung et al., 2023).

In California, constraints on rate-making, together with rising wildfire losses, drove a recent wave of insurer withdrawals (Boomhower et al., 2024; Oh et al., 2026; California Department of Insurance, 2024). In Florida, repeated tropical cyclone (TC) losses have produced insurer insolvencies, rapid premium increases, and growing reliance on the residual market (Sastry et al., 2023; Kousky & Medders, 2024; Hemmati et al., 2025). These developments raise questions about how disaster losses are redistributed when private insurance provisions contract, and whether the institutions assuming those risks have sufficient resources to finance recovery.

Despite growing recognition that climate-driven disasters pose systemic financial risks, insurance markets lack quantitative system-wide stress tests of the kind used to assess stability in banking. In the banking sector, stress testing is a central tool for evaluating the resilience of complex financial systems to rare but severe shocks, focusing on tail risks and the potential for cascading failures (Basel Committee on Banking Supervision, 2011; International Monetary Fund (IMF), 2012; Board of Governors of the Federal Reserve System, 2022). Climate-related financial-risk exercises have begun to extend this stress testing logic, building on academic proposals for climate stress testing (Battiston et al., 2017) and coordinated through the Network for Greening the Financial System (Network for Greening the Financial System (NGFS), 2024). To date, these climate applications have remained largely exploratory: the European Central Bank’s economy-wide and supervisory climate stress tests (Dunz et al., 2021; European Central Bank, 2022) and the Bank of England’s 2021 Climate Biennial Exploratory Scenario (Bank of England, 2022) carried no direct capital implications, and the U.S. Federal Reserve’s 2023 exercise was a voluntary pilot with no capital or supervisory implications (Board of Governors of the Federal Reserve System, 2024). By contrast, climate risk assessments in insurance have largely centered on catastrophe loss reporting, disclosure frameworks, and firm-level solvency exercises (Swiss Re Institute, 2024; Task Force on Climate-related Financial Disclosures, 2017; National Association of Insurance Commissioners (NAIC), 2026; European Insurance and Occupational Pensions Authority (EIOPA), 2022; Watten Håkansson et al., 2025), which are not designed to quantify when aggregate losses overwhelm market-wide capacity, trigger public backstops, or propagate across interconnected private and public actors. This gap is increasingly consequential as climate change shifts the frequency and clustering of extreme events.

Here, we develop a probabilistic, system-wide stress testing framework that assesses uninsured losses, insurer defaults, and residual financing requirements together. As an initial testbed, we apply this framework to Florida’s residential property insurance market, where high exposure to tropical cyclones, dense coastal development (Abrahams & Robustelli, 2025), and insurer insolvencies (Sastry et al., 2023) make systemic risk an immediate concern (Kousky et al., 2024). We first stress test the system using the historical hazard footprints of four damaging TCs: the Great Miami Hurricane (1926), the Lake Okeechobee Hurricane (1928), Hurricane Andrew (1992), and Hurricane Irma (2017). We complement these cases with stylized sequences of storms within a season and probabilistic event sets representing present-day and future climates. We examine how climate change, insurance coverage, market structure, and physical damage reduction affect the frequency, magnitude, and distribution of financing needs.

2 Methods

2.1 Framework and scope

We first estimate economic losses for each county and separate wind and flood contributions. We then allocate losses to private insurers, Citizens Property Insurance Corporation (Citizens hereafter), the National Flood In-

73 surance Program (NFIP), and those without sufficient insurance. Reimbursements from the Florida Hurricane
 74 Catastrophe Fund (FHCF) and catastrophe bond recoveries cover part of the insurers' claims, after which the
 75 remaining claims draw on insurers' capital. When these resources are exhausted, assessments through the
 76 Florida Insurance Guaranty Association (FIGA) and Citizens, together with federal borrowing for the NFIP,
 77 provide further financing (Fig. 1).

78 The financial model represents Florida's residential insurance market conditions in 2024. We model losses
 79 from individual historical TCs (Knapp et al., 2010), stylized sequences of events within a season, and large
 80 probabilistic event sets representing present-day and future climate conditions (Emanuel et al., 2006, 2008).
 81 The named historical storms denote hazard footprints evaluated using the study's exposure and 2024 insurance
 82 market conditions, rather than reconstructions of the original events or their realized losses. We evaluate future
 83 climate scenarios using the same 2024 insurance market configuration to isolate the effect of changing hazards.
 84 Recovery and changes in the market across successive years are not modeled.

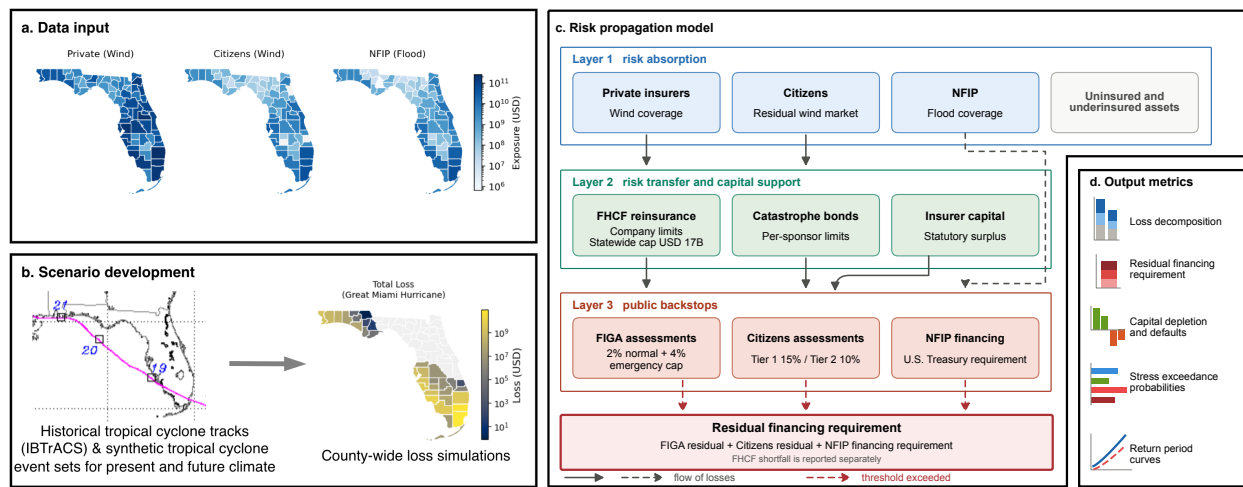


Figure 1: **Insurance system architecture and loss propagation.** (a) County exposure for private wind insurance, Citizens, and NFIP. (b) Historical and synthetic hurricane tracks produce county losses under the study's exposure and vulnerability assumptions. (c) Wind claims pass through private insurers and Citizens, with FHCF reimbursements and stylized catastrophe bond recoveries before capital depletion and assessments. NFIP follows a separate financing channel. The remaining FIGA and Citizens deficits and NFIP financing requirement form the residual financing requirement. Uninsured and underinsured losses remain outside these financing channels. (d) Outputs describe loss allocation, financing requirements, capital depletion, defaults, exceedance probabilities, and return period curves.

2.2 Hurricane hazards and economic losses

86 We use TC track data from two sources. Historical TC tracks are obtained from the International Best Track
 87 Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2010). Synthetic TC tracks are generated with
 88 the statistical-dynamical TC model developed at the Massachusetts Institute of Technology (MIT) (Emanuel
 89 et al., 2006, 2008). Present-day simulations (1980–2023) are downscaled from ERA5, the fifth-generation
 90 atmospheric reanalysis from the European Centre for Medium-Range Weather Forecasts (Hersbach et al.,
 91 2020). Future simulations use five global climate models (GCMs) from phase 6 of the Coupled Model In-
 92 tercomparison Project (CMIP6). They represent mid-century and end-of-century conditions under Shared

Socioeconomic Pathway (SSP) scenarios SSP2–4.5 and SSP5–8.5. Track generation and frequency calibration are described in Supporting Text S2.

We compute county-level TC loss estimates from these TC tracks using the open-source, probabilistic climate risk modeling platform CLIMADA (Aznar-Siguan & Bresch, 2019), which operationalizes the Intergovernmental Panel on Climate Change risk framework based on hazard, exposure, and vulnerability (IPCC, 2012) (Fig. 1b).

We use the Holland wind model (Holland, 2008) to derive a two-dimensional wind field from each TC track at a horizontal resolution of 120 arc-seconds, or approximately 4 km at the equator. The model calculates gridded 1-min sustained winds at 10 m above ground by combining the circular wind field with the translational wind speed of the storm. We use the maximum wind speed reached at each location over the lifetime of the storm as the hazard variable and exclude values below 34 kn (17.5 ms^{-1}). We do not simulate rainfall or storm surge directly. Sea-level rise is also not included in the future TC hazard sets. We represent exposed assets using the LitPop method (Eberenz et al., 2020), which spatially distributes national or subnational economic values based on population and nightlight intensity. The Florida exposure layer is calculated at the same resolution as the wind fields using gross domestic product (GDP) values from 2020.

We use regionally calibrated impact functions (also called vulnerability functions) that relate hazard intensities to relative economic damage ratios (Eberenz et al., 2021) to compute event-based loss estimates. Here, we apply the USA-specific impact function to represent macroeconomic TC losses at the state scale; sub-county variations in structural vulnerability are not explicitly modeled, consistent with the system-level focus of this analysis. Although parameterized by wind intensity, the impact functions were calibrated to observed total TC losses and therefore capture the aggregate effects of wind, rainfall, and storm surge. The resulting total loss estimates for the four historical storm scenarios (table S3) fall within the range of normalized loss estimates compiled by Muller et al. (2025).

For the probabilistic analysis, we use the event-based loss catalogs to construct 10,000 simulated hurricane seasons for each climate data set. We sample events with replacement according to the annual TC frequency of the corresponding event set and combine all events sampled within the same season. The resulting catalogs include seasons with no TC losses, a single event, and multiple events. These seasonal loss catalogs provide the input to the financial model. Supporting Text S5 describes the sampling procedure and the treatment of zero-loss and multiple-event seasons.

Because wind and flood damage are covered by different insurance programs, we divide each total loss estimate into wind and flood components. We estimate county-level wind contributions using the multi-hazard damage regression of Gori et al. (2025); Gori (2025), which yields a mean wind share of 84.6%. For each event, we sample an event-level wind share from a distribution centered on this value and rescale the county contributions accordingly. Historical storm scenarios use storm-specific wind share distributions. Supporting Text S2 details the rescaling procedure and historical wind share distributions.

2.3 Insurance exposure and loss allocation

We allocate county-level residential wind insurance exposure to private insurers and Citizens using their total insured values (Fig. 1a). Private market exposure comes from FHCF reports, while Citizens provides its own county-level records (Florida Hurricane Catastrophe Fund, 2024b; Citizens Property Insurance Corporation, 2024b). Because insurer-specific county portfolios are not publicly available, we allocate private market exposure among the 100 largest insurers in proportion to their statewide residential premiums (Florida Office of Insurance Regulation, 2024). Applying the same premium shares in every county preserves the statewide market composition but does not capture differences in insurers' geographic concentration. We use statutory

surplus reported for individual insurers and affiliated groups, obtained through S&P Capital IQ, as available capital. Supporting Text S1 documents the inputs and their reference dates.

We represent the share of wind losses covered by insurance with a Beta(4,6) distribution, which has a mean of 0.40. We base this distribution on Florida insured losses, NFIP payments, and reconstructed total economic losses for 2017–2024 (Supporting Text S3). The resulting ratio measures insured losses reported by the Florida Office of Insurance Regulation as a share of total economic loss rather than the proportion of residential properties with wind coverage. We therefore use it as an allocation assumption rather than a direct estimate of residential wind insurance penetration. We allocate insured wind losses among private insurers and Citizens according to their county-level exposure. The balance combines uninsured or underinsured residential losses with losses to nonresidential assets included in the economic exposure. The model does not distinguish between these two sources.

For flood losses, we use the Federal Emergency Management Agency’s NFIP Residential Penetration Rates dataset to estimate the proportion of residential structures with NFIP coverage in each county ([Federal Emergency Management Agency \(FEMA\), 2025](#)). The rates use the residential stock estimated by the National Structure Inventory as their denominator. We combine rates inside and outside Special Flood Hazard Areas according to their shares of the county’s residential stock. We apply the resulting county penetration rate to flood losses and cap claims at the county’s NFIP coverage in force ([Federal Emergency Management Agency \(FEMA\), 2024](#)). This assumes that NFIP-insured structures account for the same share of county flood losses as their share of the residential stock. Supporting Text S3 details the calculation and its limitations.

2.4 Risk transfer, capital depletion, and institutional backstops

The FHCF reimburses participating wind insurers for eligible claims above a retention, the amount they must first absorb themselves. For each company, we aggregate losses across all counties before applying its retention. We then apply its coverage election and a 10% loss adjustment expense allowance and cap the resulting reimbursement at the company-specific limit ([Florida Hurricane Catastrophe Fund, 2023a, 2023b, 2024a](#)). Total FHCF recoveries across private insurers and Citizens cannot exceed the modeled seasonal capacity of USD 17 billion. If requested recoveries exceed this capacity, we reduce them proportionally across private insurers and Citizens. Although the contract defines terms by company and covered event, our seasonal approximation applies them once to each company’s aggregate seasonal losses.

Catastrophe bonds provide additional recoveries through stylized layers assigned to identified insurers. We use reported bond principal from the Artemis deal directory ([Artemis.bm, 2024](#)). For each bond, we set both the attachment and maximum payout equal to its principal and apply the layer once to the beneficiary’s aggregate wind claims after FHCF reimbursement, without reinstatement. Other private reinsurance treaties are not included. We subtract these recoveries from insured wind losses and deduct the remaining claims from statutory surplus. An insurer with negative surplus may receive support from an affiliated group, subject to available capital and an eligibility rule. Insurers that remain in deficit are classified as insolvent. This represents the exhaustion of modeled capital rather than a regulatory liquidation decision. Supporting Text S4 specifies the risk transfer assumptions, capital accounting, and support rule.

For private insurers classified as insolvent, we aggregate the remaining deficits and compare them with one year of modeled FIGA assessment capacity. This capacity comprises 2% normal and 4% emergency assessments of surviving insurers’ written premiums ([State of Florida, 2024; FIGA, 2026](#)). Any deficit beyond this capacity is recorded as a FIGA residual deficit.

For Citizens, claims remaining after modeled recoveries draw on statutory surplus ([Citizens Property Insurance Corporation, 2024a](#)). Two assessment tiers then provide financing, limited to 15% of Citizens’ premium

base and 10% of the statewide property premium base ([Citizens Property Insurance Corporation, n.d.](#)). We record any deficit remaining after both tiers as a Citizens residual deficit. Assessments spread costs among insurers and policyholders. The model does not assign the remaining deficits to a final payer or model borrowing backed by future assessment streams.

NFIP claims first draw on a national fund balance of USD 3.441 billion ([Congressional Research Service, 2025](#)). We record Florida claims beyond this balance as an NFIP financing requirement. Assigning the full national fund balance to Florida without accounting for claims from other states can understate financing needs, whereas omitting NFIP reinsurance can overstate them when recoveries would apply. We do not cap the financing requirement at the USD 9.9 billion of remaining NFIP borrowing authority reported for October 2024 ([Congressional Research Service, 2025](#)). The metric therefore measures funding needed beyond the modeled fund balance, including amounts that may exceed the borrowing capacity available at the study baseline.

Supporting Text S4 provides the full equations for risk transfer, capital depletion, group support, and institutional backstops. Table S8 lists the corresponding parameter values. An overview of the risk propagation model is provided in Fig. 1c.

2.5 Scenario design and analysis

We selected the four historical storms as recognizable, high-consequence analogues spanning different hazard profiles and historical periods. To examine the effects of multiple storms within a season, we also construct three two-storm scenarios: Great Miami followed by Andrew, repeated Great Miami, and repeated Irma.

We evaluate each historical storm and each two-storm scenario using 1,000 parameter realizations. In each two-storm scenario, the first storm reduces exposed asset values before losses from the second storm are calculated. Vulnerability remains unchanged, and damaged exposure is not repaired between storms. We then sum the losses from both storms by county and apply the financial model once to the combined losses. These scenarios therefore capture exposure depletion but not event-by-event changes in financial resources. The resulting losses and financial outcomes are summarized in table S3.

For the probabilistic assessment, we evaluate each of the 10,000 synthetic seasons described above independently, using the same initial financial resources. Supporting Text S5 describes the sampling and aggregation.

To assess systemic risk under future climate conditions, we focus on SSP2–4.5 and report results for SSP5–8.5 in the Supporting Information (SI). For each GCM and future period, we calculate the change in each outcome relative to the corresponding historical simulation. For monetary outcomes and the number of insurer defaults, we subtract the mean across the historical seasons from the mean across the future seasons. For threshold indicators, we calculate the difference between the annual exceedance probabilities in the historical and future simulations. We take the median change across the five GCMs and add it to the ERA5 baseline. Changes in exceedance probabilities are expressed in percentage points. Supporting Text S5 provides the equations and further details.

We also analyze how changes in physical losses, insurance coverage, and market structure affect systemic risk. We first reduce wind losses by 30% and flood losses by 25% to represent potential effects of stronger building standards and retrofitting. We then evaluate combinations of wind and flood loss reductions to determine how much damage would need to be avoided to offset the mid-century effects of SSP2–4.5. To examine expanded insurance coverage, we raise the insured wind fraction from 40% to 60% and the target NFIP participation rate from approximately 11% to 30%, with corresponding changes in exposure, premiums, capital, and Citizens' share. Finally, we simulate further contraction of the private market by increasing Citizens' target share from 15% to 25% while holding initial capital, premium inputs, and the insured wind fraction

fixed. Supporting Text S5 provides the full scenario settings.

2.6 Outcome metrics

We track how economic losses are allocated among private insurers, Citizens, the NFIP, and uninsured or underinsured assets, together with private insurer defaults and the largest entity deficit (Fig. 1d). Institutional stress indicators record whether modeled capacities are exhausted and compare NFIP claims with Florida premium income and the residual financing requirement with Florida GDP. Table S2 defines the indicators and their thresholds.

For each season, the residual financing requirement is the sum of the FIGA residual deficit, the Citizens residual deficit, and the NFIP financing requirement. FHCF recoveries and any statewide reimbursement shortfall are reported separately. We do not add the FHCF shortfall to the residual financing requirement because an unreimbursed claim already reduces insurer capital and may contribute to a subsequent FIGA or Citizens deficit. Adding it again would count that loss twice. The aggregate describes financing needs across institutions rather than government expenditure or the final distribution of costs.

Annual exceedance probabilities are the fractions of simulated seasons that meet a specified condition, and return periods are their inverse. For a return period T , we estimate the return level as the empirical $1 - 1/T$ quantile of the corresponding outcome across the 10,000-season loss catalog, including seasons with zero loss. The residual financing requirement is summed within each season before estimating its return level. We estimate the return levels of total economic loss and the residual financing requirement separately. Their comparison describes how the two marginal tails increase as events become rarer rather than comparing paired outcomes from the same season. Supporting Text S6 provides the estimator and amplification calculation.

2.7 Uncertainty and model evaluation

To represent uncertainty in loss attribution and insurer portfolios, we sample the wind share of each event (Supporting Text S2), the insured wind fraction (Supporting Text S3), and insurer exposure within counties (Supporting Text S6). For the latter, we independently vary each insurer's estimated total insured value within each county. The draws are centered on the input value, with a standard deviation equal to 15% of that value. The sampled values determine how insured wind losses are distributed among private insurers and Citizens but do not change the county's total insured wind loss. All other financial inputs remain fixed in the baseline analysis. Moreover, we perform a sensitivity analysis in which the insured wind fraction is fixed at values from 0.1 to 0.5 (Table S6). Table S8 distinguishes sampled inputs, fixed assumptions, and variation across climate models.

We quantify sampling uncertainty in ERA5 return levels and annual exceedance probabilities using 1,000 bootstrap resamples of complete seasons. Future climate results report the 10th to 90th percentile range of changes across the five GCMs. These intervals represent sampling uncertainty and variation across climate models, respectively, but do not capture all structural uncertainties. Supporting Text S6 provides more detail.

3 Results

3.1 Stress testing the insurance system with historical and sequential events

Across the historical and sequential stress-test scenarios, approximately 61–77% of economic losses remain uninsured or underinsured (Fig. 2a), with the highest share occurring in the flood-heavy Lake Oke-

chobee scenario. The mean residual financing requirement reaches USD 10.4 billion for Hurricane Andrew, USD 15.0 billion for the Lake Okeechobee Hurricane, and USD 22.4 billion for the Great Miami Hurricane. Sequential scenarios generate requirements of USD 45.4 billion for Great Miami followed by Andrew and USD 57.6 billion for repeated Great Miami. Both exceed the sum of the corresponding individual-event requirements, even though damage from the first storm reduces the assets exposed to the second. By contrast, Hurricane Irma produces a much smaller residual financing requirement of USD 0.16 billion, increasing to USD 2.2 billion when the storm is repeated. These differences reflect the magnitude of insured losses reaching the backstops rather than total losses alone. Although Irma's total losses are substantial, much of its flood loss remains uninsured, limiting the losses absorbed by the insurance system.

FHCF reimbursements reduce retained wind claims before FIGA and Citizens deficits are calculated (table S3). The statewide FHCF cap does not bind in these scenarios because the combined company reimbursement limits remain below its USD 17 billion capacity, although individual company limits can still be reached.

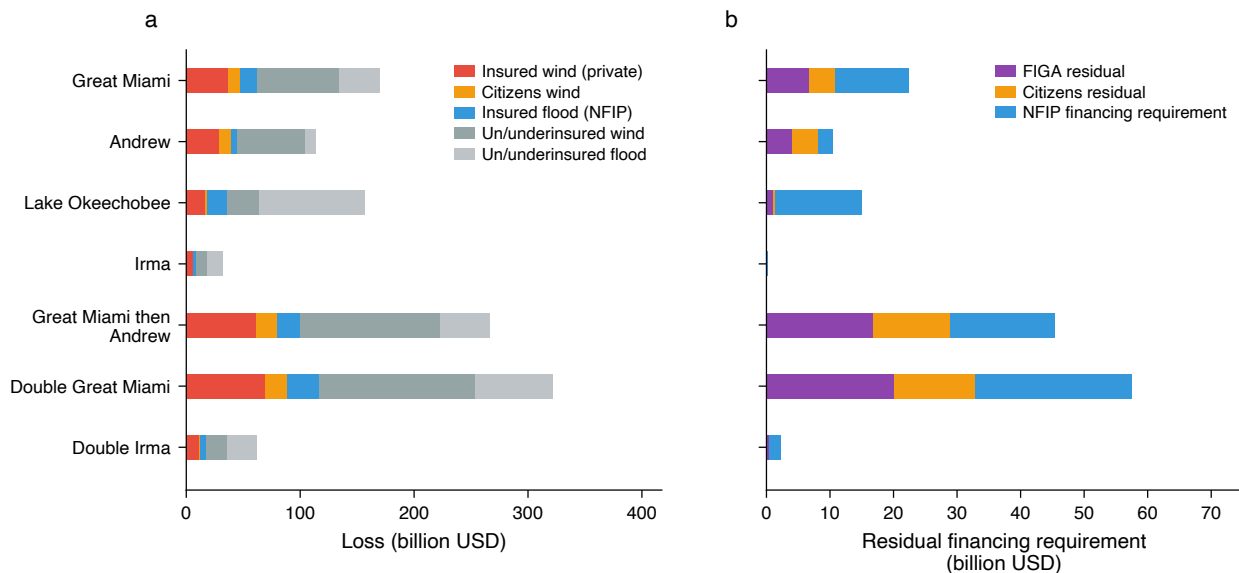


Figure 2: **Loss decomposition and residual financing requirements across historical and sequential TC scenarios.** (a) Decomposition of mean economic losses across insured wind (private insurers and Citizens), insured flood (NFIP), and uninsured or underinsured losses. (b) Mean residual financing requirement, comprising FIGA and Citizens residual deficits and the NFIP financing requirement. Monetary values are in billion USD. Each scenario contains 1,000 realizations; a complete tabulation, including uncertainty ranges, is provided in table S3. Named storms denote historical hazard footprints evaluated under the study's exposure and insurance market assumptions, not reconstructions of the original events or their realized losses.

3.2 Probabilistic assessment of systemic insurance risks

Moving beyond individual scenarios, we quantify systemic insurance risk probabilistically using a catalog of 10,000 simulated TC seasons. Table 1 places the scenario-based stress tests into a probabilistic context by reporting economic losses and financing requirements at selected return periods under the ERA5 climate baseline. A total seasonal economic loss comparable to the Great Miami stress test, approximately USD 170.4 bil-

lion, corresponds to an empirical return period of approximately 31 years. Great Miami followed by Andrew and repeated Great Miami correspond to economic loss return periods of approximately 55 and 79 years, respectively.

The probabilistic results reveal a more than proportional increase in residual financing requirements across return periods (Fig. 3). For each return period, we compare the estimated financing requirement with the corresponding estimate of total seasonal economic loss. If these quantities increased proportionally, the relationship would follow a constant-share reference line. Instead, the financing requirement rises much more steeply. While total economic losses increase by approximately a factor of nine between return periods of 10 and 100 years, from USD 39.5 to 357.2 billion, the financing requirement increases by a factor of approximately 88, from USD 0.65 to 57.3 billion (Table 1). A power relationship fitted across the seven reported return periods has an exponent of 1.86. The economic loss and financing estimates at each return period are calculated separately, so the comparison describes their distributions rather than paired outcomes from individual seasons.

In most seasons, no residual financing requirement remains under the modeled financing rules. The requirement is zero in 84.8% of simulated seasons and positive in 15.2%, corresponding to an empirical return period of approximately 6.6 years.

At return periods of 25 years and longer, FIGA residual deficits constitute the largest marginal component of the financing requirement. At a return period of 100 years, the FIGA residual deficit is USD 34.2 billion, exceeding both the Citizens residual deficit of USD 15.5 billion and the NFIP financing requirement of USD 10.3 billion. These component estimates are calculated separately and do not sum to the aggregate financing requirement at the same return period. FHCF statewide reimbursement shortfall remains zero under the company limits described above.

Grouping seasons by total economic loss provides a complementary comparison of the institutions' contributions. The mean residual financing requirement increases from 4.9% of mean economic loss for seasons with losses corresponding to return periods of approximately 10–25 years to 18.4% for seasons with losses above the 100-year threshold. FIGA accounts for the largest component in every group above the loss threshold corresponding to a return period of approximately 10 years, followed by Citizens and the NFIP (Fig. S4).

The probabilistic approach further allows us to assess the annual exceedance probabilities of systemic risk thresholds that indicate stress across different components of the insurance system (Fig. 4a, table S5). For the private wind insurance market, the annual probability of more than ten insurer defaults is 8.7%, while the probability that the largest single-entity deficit exceeds USD 1 billion is 5.6%.

For public and quasi-public institutions, the annual probabilities that FIGA and Citizens require financing beyond their modeled assessment capacities are 13.7% and 13.6%, respectively. For the NFIP, the probability that Florida claims exceed twice Florida NFIP annual premium income is 5.0%.

Finally, we relate the aggregate financing requirement to the economic scale of Florida, using GDP of USD 1.7 trillion as a reference. The annual probability that the requirement exceeds 1% of Florida's GDP is 3.4%, while the probability of exceeding 10% is 0.08%. These amounts describe unmet financing needs across institutions rather than government expenditure.

Table 1: **Economic losses and residual financing requirements at selected return periods.** Columns show return periods in years, and monetary values are in billion USD. Each entry is an empirical estimate for a seasonal outcome, calculated from all 10,000 simulated seasons. The aggregate financing requirement is calculated within each season as the sum of FIGA and Citizens residual deficits and the NFIP financing requirement before estimating the amount associated with each return period. Component estimates are calculated separately and are not additive.

Metric (USD B)	10	25	50	100	250	500	1000
Total loss	39.5	146.9	246.4	357.2	563.9	628.0	738.0
Insured wind, private	11.6	41.8	69.7	103.2	155.2	198.4	214.3
Citizens wind	1.8	6.8	14.5	22.1	35.6	53.6	62.9
Insured flood, NFIP	0.9	3.7	7.4	13.7	26.1	37.6	50.3
Un/underinsured wind	19.8	71.8	125.9	183.1	257.6	321.1	392.1
Un/underinsured flood	3.9	15.1	28.4	47.1	87.3	112.7	141.7
Residual financing requirement	0.7	12.6	32.3	57.3	98.9	136.7	163.7
FIGA residual deficit	0.4	8.5	20.4	34.2	56.1	74.0	82.7
Citizens residual deficit	0.2	0.5	7.9	15.5	29.0	47.0	56.4
NFIP financing requirement	0.0	0.2	4.0	10.3	22.7	34.1	46.8

3.3 Systemic risk probabilities increase with climate change

We next evaluate how projected changes in TC hazard alter systemic insurance risk, holding exposure, capital positions, and institutional rules at their baseline values. The main analysis focuses on SSP2–4.5 for mid-century (2041–2060) and end-of-century (2081–2100), with SSP5–8.5 results provided in the SI. Future changes are estimated using a multi-model delta approach. For each risk metric, the median of the future-minus-historical changes across five GCMs is added to the ERA5 baseline (Section [Scenario design and analysis](#)). The changes reported below therefore isolate the response of the modeled insurance system to climate-driven shifts in the TC loss distribution.

Under mid-century SSP2–4.5, expected annual economic losses increase from USD 19.3 to 48.5 billion, and the mean residual financing requirement increases from USD 2.1 to 5.5 billion (table S4). Exceedance probabilities of systemic stress thresholds increase across the private market and institutional backstops (Fig. 4a, table S5). The annual probability of more than ten private insurer defaults rises from 8.7% under baseline conditions to 21.1%.

The probability that FIGA’s modeled assessment capacity is exceeded increases from 13.7% to 32.2%, while the corresponding probability for Citizens rises from 13.6% to 31.3%. For the NFIP, the annual probability that Florida claims exceed twice Florida NFIP annual premium income increases from 5.0% to 12.8%.

At the aggregate level, the annual probability that the residual financing requirement exceeds 1% of Florida’s GDP increases from 3.4% at baseline to 8.7% by mid-century and 11.7% by end-of-century. The mean financing requirement reaches USD 7.2 billion by end-of-century (table S4). Exceedance of 10% of GDP remains less frequent, with annual probabilities of 0.14% and 0.20% for the two future periods, respectively, compared with 0.08% at baseline.

Uncertainty across climate models remains substantial (table S5). For example, the mid-century probability of FIGA capacity exceedance ranges from 17.0% to 42.2% over the reported 10th–90th percentile interval across GCM changes, compared with a baseline probability of 13.7%. The full set of estimates and intervals

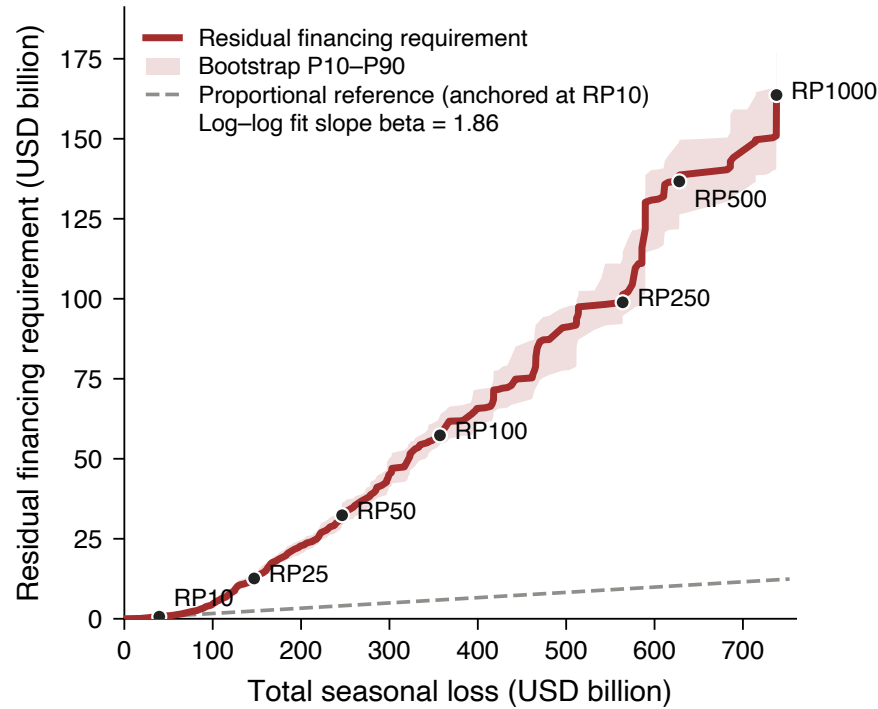


Figure 3: **Residual financing requirement increases more steeply than economic loss across return periods.** Points compare the economic loss and financing requirement estimates at the return periods reported in Table 1, based on 10,000 simulated TC seasons under the ERA5 climate baseline and the 2024 insurance market configuration. RP labels indicate return periods in years. The points do not represent paired outcomes from individual seasons. The dashed line shows a proportional, constant-share reference anchored at the estimates for a return period of 10 years. The fitted power relationship across the seven points has an exponent of 1.86. Shading shows the pointwise 10th–90th percentile bootstrap interval for the financing requirement at each return period from 1,000 resamples of complete seasons. Economic loss estimates are held at their full-sample values, so horizontal uncertainty is not displayed. The financing requirement comprises FIGA and Citizens residual deficits and the NFIP financing requirement.

for both future periods and climate scenarios is provided in table S5.

3.4 Systemic risks with evolving markets and insurance policies

We next evaluate how changes in market structure and insurance policies modify systemic risk under present-day hazard conditions. The three stylized interventions represent private market contraction and expansion of residual markets following insolvencies and insurer withdrawals (Hemmati et al., 2025; California Department of Insurance, 2024; Kousky & Medders, 2024), expanded insurance coverage to reduce protection gaps (Kousky et al., 2024), and strengthened building codes and retrofitting initiatives aimed at reducing physical losses (Wolf & Takeuchi, 2025; Insurance Institute for Business & Home Safety, 2025). These analyses assess the system’s response to prescribed changes rather than predict specific policy outcomes (Section Scenario design and analysis).

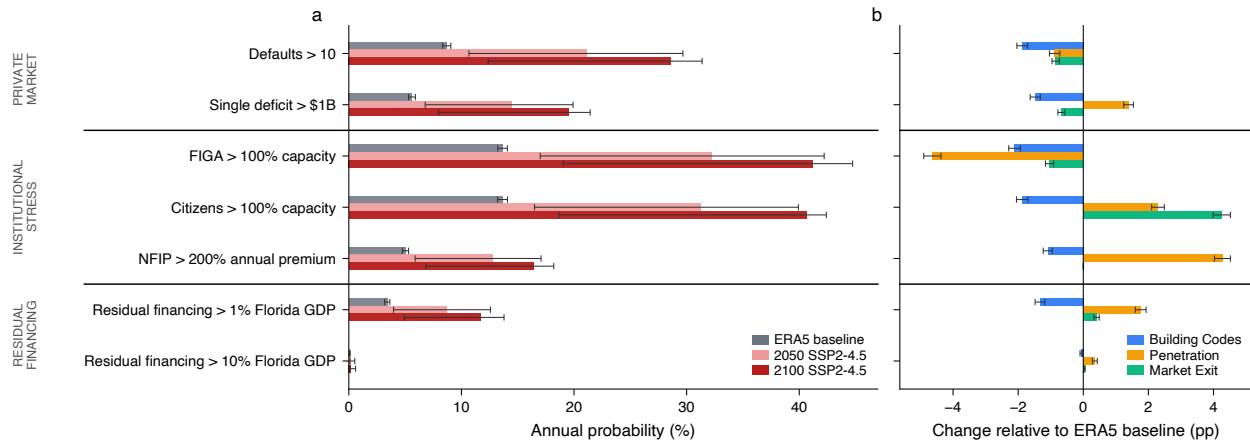


Figure 4: Probabilistic assessment of systemic insurance risks under future climate scenarios and stylized policy interventions. Annual exceedance probabilities of systemic stress thresholds for private insurers (top), institutional backstops (middle), and the residual financing requirement relative to Florida GDP (bottom). (a) Annual probabilities under the ERA5 baseline and mid-century and end-of-century SSP2–4.5. Each future estimate adds the median future-minus-historical change in the indicator probability across five GCMs to its ERA5 probability. Future error bars show the corresponding 10th–90th percentile range of GCM changes added to the ERA5 baseline. (b) Percentage-point (pp) changes relative to ERA5 under private insurer market exit, increased insurance penetration, and prescribed reductions in physical losses. Error bars show the 10th–90th percentile interval from 1,000 paired bootstrap resamples of complete seasons. Positive values indicate increased exceedance probability, and negative values indicate a reduction. All probabilistic analyses use 10,000 seasons. For FIGA and Citizens, capacity exceedance denotes a positive residual deficit after modeled assessments. SSP5–8.5 comparisons are provided in Fig. S3.

Private insurer market exit We model a contraction of the private wind market that increases Citizens’ target share from 15% to 25% of total insured value while holding initial insurer capital, premium inputs, and the insured wind fraction fixed. Under this scenario, the annual probability of more than ten private insurer defaults declines by 0.9 percentage points relative to the ERA5 baseline (Fig. 4b, table S5), reflecting the reduced exposure and insured loss volume within the private market. However, financing pressure increases at Citizens, whose probability of exceeding its modeled assessment capacity rises by 4.3 percentage points. The mean residual financing requirement increases from USD 2.1 to 2.4 billion (table S4), and its probability of exceeding 1% of Florida’s GDP rises by 0.4 percentage points (table S5).

Insurance penetration increase We increase the assumed insured wind fraction from 40% to 60% and the target NFIP participation rate from approximately 11% to 30%, with corresponding adjustments to capital, premiums, and market allocation (Supporting Text S5). While expanded coverage reduces mean uninsured and underinsured losses from USD 12.1 to 7.9 billion (table S4), its systemic effects differ across institutions. The annual probability that Florida NFIP claims exceed twice Florida NFIP annual premium income increases by 4.3 percentage points relative to the ERA5 baseline, despite the expansion of the premium base (Fig. 4b, table S5). The probability that Citizens exceeds its modeled assessment capacity increases by 2.3 percentage points, and the probability that the residual financing requirement exceeds 1% of Florida’s GDP increases by 1.8 percentage points. The mean financing requirement rises from USD 2.1 to 4.2 billion (table S4).

Other indicators decline. The annual probability of more than ten private insurer defaults decreases by 0.9

percentage points, while FIGA capacity exceedance decreases by 4.6 percentage points (table S5). However, the probability that the largest single-entity deficit exceeds USD 1 billion rises from 5.6% to 7.0%. Expanded coverage therefore narrows the protection gap without uniformly reducing financial stress, even with the prescribed increases in capital and premiums.

Building code improvement We evaluate a stylized scenario in which stronger building codes and retrofiting are assumed to reduce wind losses by 30% and flood losses by 25% before insurance allocation. Expected annual economic losses fall from USD 19.3 to 13.7 billion, and the mean residual financing requirement decreases from USD 2.1 to 1.2 billion (table S4). Exceedance probabilities decline across private insurers and institutional backstops (Fig. 4b, table S5). The annual probability of more than ten private insurer defaults decreases by 1.9 percentage points relative to the ERA5 baseline, FIGA capacity exceedance decreases by 2.1 percentage points, and Citizens capacity exceedance decreases by 1.9 percentage points. The probability that the financing requirement exceeds 1% of Florida’s GDP declines by 1.3 percentage points. Reducing physical losses thus lowers financing needs across the modeled insurance system.

We also vary paired wind and flood loss reductions under mid-century SSP2–4.5 to determine when the mean residual financing requirement returns to the ERA5 baseline. This occurs at prescribed wind and flood loss reductions of approximately 84% and 56%, with an unweighted arithmetic mean of 70.0% (Fig. 5). At this point, expected annual economic loss falls from USD 48.5 billion without loss reduction to USD 23.3 billion, a reduction of approximately 52%. Thus, with the insurance market held fixed, roughly halving economic losses relative to unmitigated mid-century conditions offsets the modeled increase in mean financing needs. Returning the mean number of private insurer defaults and mean economic loss to their ERA5 baselines requires similar mean prescribed reductions of 76.3% and 78.0%, respectively (Figure S2). These reductions are stylized assumptions about avoided damage rather than estimates of the performance or implementation costs of particular building standards. Supporting Text S5 details the prescribed reduction pairs and interpolation procedure.

4 Discussion

Insurance market stability depends on how disaster losses are distributed and financed, as well as on their total magnitude. Climate scenario analyses already examine risks to insurers and the wider financial system (Bank of England, 2022; European Insurance and Occupational Pensions Authority (EIOPA), 2022). By linking probabilistic tropical cyclone losses to insurance coverage, insurer capital, risk transfer, and institutional financing rules, our framework assesses uninsured losses, insurer defaults, and residual financing requirements together. Its application to Florida shows how these outcomes respond to changes in hazard, coverage, and physical vulnerability in a region with high hurricane exposure (Blake et al., 2011) and a market-oriented public–private insurance system (Grace & Klein, 2009).

Residual financing requirements increase more steeply than economic losses across the reported return periods. Between return periods of 10 and 100 years, the financing requirement increases approximately 88-fold, compared with a ninefold increase in economic loss (Fig. 3). Our analysis complements qualitative scenarios of systemic insurance risk (Kousky et al., 2024) by quantifying the frequency and magnitude of residual financing needs. Under present-day conditions, FIGA and Citizens each retain a deficit after assessments in roughly one in seven simulated seasons, with FIGA showing the largest institutional residual deficit at a return period of 100 years. An insurance system may meet claims in most seasons yet face substantial financing

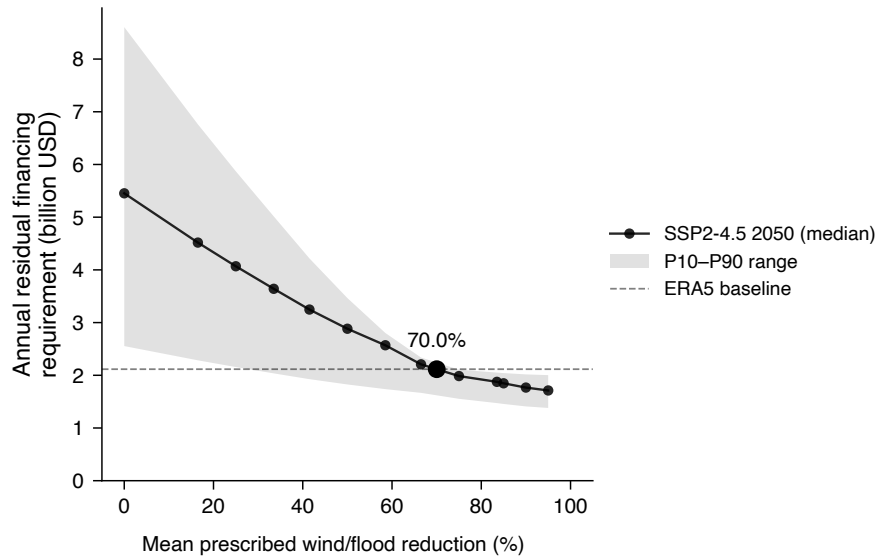


Figure 5: Physical loss reductions required to offset mid-century climate effects on the residual financing requirement. Sensitivity of the mean residual financing requirement to prescribed wind and flood loss reductions under mid-century SSP2–4.5 (2041–2060). The horizontal axis shows the unweighted arithmetic mean of each prescribed wind and flood reduction pair, rather than the resulting percentage reduction in total economic loss. The solid curve adds the median future-minus-historical change across five GCMs to the ERA5 mean. Shading shows the corresponding 10th–90th percentile range across GCM changes, and the dashed line marks the ERA5 baseline. The black circle marks the interpolated return to the baseline financing requirement at an arithmetic mean prescribed reduction of 70.0%. Each analysis uses 10,000 simulated TC seasons. Only nonnegative financing requirements are displayed. Corresponding results for mean economic loss and private insurer defaults are shown in Figure S2.

gaps in severe years. Preparedness therefore depends on the frequency, size, and institutional distribution of financing needs, as well as economic losses.

Climate change increases these financing pressures even when exposure and the insurance market are held fixed. Under mid-century SSP2–4.5, mean residual financing requirement rises from USD 2.1 to 5.5 billion, alongside increases in insurer defaults and institutional capacity exceedance. Responses such as premium increases and coverage restrictions can protect insurers’ financial positions while making insurance less accessible (Bank of England, 2022). Maintaining insurance market stability under climate change therefore requires attention to both the resources available to meet claims and the continued availability of financial protection (Surminski et al., 2016; European Central Bank & European Insurance and Occupational Pensions Authority, 2024).

Expanded coverage lowers mean uninsured and underinsured losses from USD 12.1 to 7.9 billion, while increasing mean residual financing requirement from USD 2.1 to 4.2 billion. The additional financing need accompanies a narrowing of the protection gap, an important outcome given evidence of widespread flood underinsurance and the role of insurance in supporting recovery (Amornsiripanitch et al., 2025; Kousky, 2019). In our market exit scenario, private insurer defaults decline while financing pressure at Citizens increases as insured exposure shifts toward the residual market. Public insurance schemes can preserve coverage when private provision contracts, but sustaining this role requires resources commensurate with the risks they assume (Jarzabkowski et al., 2023). Insurance prices and availability can communicate underlying risk, whereas sub-

sidized or publicly backstopped coverage that preserves affordability without reducing exposure can weaken incentives for mitigation and encourage continued development in high-risk areas (Ben-Shahar & Logue, 2016; Kousky & Kunreuther, 2014; Burby, 2006; Peralta & Scott, 2024).

The modeled statewide FHCF reimbursement shortfall is zero because the combined company limits remain below the statewide cap. Meeting reimbursement obligations can nevertheless spread costs across policyholders and over many years. Following Hurricane Wilma in 2005, the FHCF borrowed USD 2.65 billion, which was repaid through emergency assessments on Florida property and casualty policyholders that ended in January 2015 (Florida Hurricane Catastrophe Fund, 2025).

Physical damage reduction lowers both economic losses and the demands placed on insurance institutions. Evidence from Florida's statewide building code and the voluntary FORTIFIED standard shows that stronger construction can reduce wind damage and insured losses (Simmons et al., 2018; Wolf & Takeuchi, 2025; Alabama Department of Insurance and Center for Risk and Insurance Research, 2025). In our stylized mid-century SSP2-4.5 analysis, reducing expected annual economic loss by approximately 52% relative to the unmitigated future level returns the mean residual financing requirement to its present-day baseline (Fig. 5). These findings support considering stronger construction and retrofitting alongside arrangements for financing the remaining losses (New et al., 2022).

The required loss reductions vary substantially across the climate-model ensemble. Previous analysis of relative changes in TC risk using the MIT TC model found that choice of GCM contributed more uncertainty than choice of emissions scenario (Meiler et al., 2023). This uncertainty ranking applies to that modeling framework and should not be generalized to other TC models or climate extremes. Adaptation planning should therefore evaluate measures across a range of hazard projections, including the additional reductions needed under higher-loss outcomes.

Our assessment of Florida's hurricane-exposed insurance market provides a template for comparing how insurance systems distribute disaster losses and respond to climate change and adaptation. Public and private insurance arrangements vary widely across countries (Jarzabkowski et al., 2023), so applications elsewhere must reflect local hazards, vulnerability, insurer portfolios, and financing rules.

Several simplifications affect estimated financing needs and their distribution across institutions. Applying statewide private insurer shares uniformly across counties does not capture geographic heterogeneity in insurers' portfolios and may alter which insurers default. Omitting private reinsurance leaves more losses on insurer balance sheets where those contracts would otherwise provide recoveries. The insured wind fraction is calibrated against economic losses and then applied to wind loss, while residential flood participation is applied to a broader economic exposure. The NFIP representation assigns the national fund balance to Florida while omitting claims from other states, NFIP reinsurance, and the statutory borrowing limit. More detailed insurer portfolios, coverage information, and reinsurance contracts would improve the representation of these financing channels.

The framework also simplifies physical hazards and financial responses over time. Wind and flood losses are partitioned using an external multi-hazard regression, and future flood losses do not account for sea-level rise. Financial calculations use aggregated seasonal losses and do not resolve the timing of claims or capital replenishment between events. Future climate analyses hold the 2024 market configuration fixed, excluding endogenous changes in premiums, coverage, and insurer participation. Extending the framework to explicit flood modeling and financial adjustment over multiple years would strengthen its use for assessing adaptation and insurance policies.

5 Conclusions

By embedding probabilistic hazard realizations within a market-wide representation of insurance coverage, insurer capitalization, and public backstops, this study provides a quantitative framework for evaluating how climate-driven disaster losses propagate through insurance systems. Its application to Florida shows that residual financing requirements rise more steeply than economic losses across return periods, concentrate within particular institutions, and shift across actors as coverage and market structure change. Projected changes in tropical cyclone hazard increase stress on the present-day insurance arrangement, while physical damage reduction lowers both economic losses and financing needs. When adapted to local hazards and financing rules, the framework can support stress testing and policy comparisons in other climate-exposed insurance markets. Future work linking uninsured losses to housing, credit, and public finance could extend this assessment to wider economic consequences. More broadly, insurance resilience depends on reducing underlying risk, preserving access to recovery finance, and ensuring that institutions assuming risk have sufficient resources.

Acknowledgments

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Author Contributions

Conceptualization: SM, SIJ

Methodology: SM

Visualization: SM

Datasets: SM, SIJ, KE

Writing - original draft: SM

Writing - review & editing: SM, SIJ, KE, NSD, JWB

Conflict of Interest

KE is the Chief Scientific Officer of WindRiskTech, LLC, which owns the synthetic tropical cyclone data used in this study. He also serves on the boards of Trusted Resource Underwriters and Plymouth Rock Home, which insure homeowners in several U.S. states. The other authors declare no competing interests.

501 Use of Artificial Intelligence Tools

502 OpenAI’s ChatGPT was used for language editing; Anthropic’s Claude Code for code review and debugging.
503 The authors are responsible for the analyses, interpretations, and final manuscript.

504 Open Research Statement

505 The Florida insurance risk model is openly available under the GNU General Public License v3.0 at
506 https://github.com/simoneileir/systemic_insurance_risk_fl_pub. Archived software releases
507 are available through Zenodo (Meiler, 2026). The repository includes public financial and regulatory inputs,
508 historical-event loss files, a demonstration using synthetic insurer data, and scripts for the simulations and
509 publication figures and tables. The hazard preprocessing used CLIMADA v6.1.0-dev with Python 3.11 or
510 later. CLIMADA is open-source software (Aznar-Siguan & Bresch, 2019; Siguan et al., 2025). The public
511 tropical cyclone hazard and damage dataset used to derive wind–flood attribution is archived on DesignSafe
512 (Gori, 2025). Other public data sources are identified in the Methods and Supporting Information.

513 Full recomputation requires two restricted inputs. Company-level market shares and statutory surplus data
514 from S&P Capital IQ require a commercial license obtained from S&P Global. Synthetic tropical cyclone
515 event sets from the MIT model are owned by WindRiskTech, LLC and cannot be redistributed by the authors.
516 Access for research must be arranged with WindRiskTech at info@windrisktech.com, subject to its access
517 and non-redistribution terms. Derived event-level files are subject to the same restrictions.

Supporting Information

Contents of this file

1. Texts S1–S6
2. Tables S1–S8
3. Figures S1–S4

Introduction This Supporting Information provides the data sources, model equations, model choices and assumptions, and uncertainty analyses underlying the study, together with supplementary tables and figures. References cited here are included in the main manuscript.

Text S1 Data sources

Insurance exposure and coverage

We assemble the insurance market inputs from statutory filings, regulatory reports, and administrative datasets. The financial inputs describe conditions in 2024, with Florida Hurricane Catastrophe Fund (FHCF) terms from the 2023–2024 contract. Table S7 lists the key model parameters and their uncertainty treatment in the simulations.

For the private admitted market, county total insured value (TIV) comes from the FHCF 2024 annual exposure report ([Florida Hurricane Catastrophe Fund, 2024b](#)). We allocate this residential wind exposure among the top 100 individual insurers according to their statewide residential direct premiums written in 2024. The premium data come from National Association of Insurance Commissioners (NAIC) annual statements accessed through S&P Capital IQ and Florida Office of Insurance Regulation (FLOIR) market share reports ([Florida Office of Insurance Regulation, 2024](#)). Each insurer therefore has the same relative share of the private market in every county. This assumption preserves the observed statewide market shares but does not represent geographic heterogeneity in insurers' portfolios. Insurer exposure by county is not publicly available. Its protection as a trade secret was upheld in *Office of Insurance Regulation v. State Farm Florida Insurance Co.* ([Florida First District Court of Appeal, 2017](#)).

Citizens Property Insurance Corporation, hereafter Citizens, publishes county exposure directly. We use its policies in force and exposure as of September 30, 2024, including multiperil homeowners and residential wind-only policies ([Citizens Property Insurance Corporation, 2024b](#)).

National Flood Insurance Program (NFIP) coverage in force and written premiums come from the Federal Emergency Management Agency (FEMA) OpenFEMA data for policy year 2024 ([Federal Emergency Management Agency \(FEMA\), 2024](#)). County participation rates use FEMA estimates of insured residential structures relative to all residential structures within and outside Special Flood Hazard Areas (SFHAs) ([Federal Emergency Management Agency \(FEMA\), 2025](#)). We apply these rates to the county flood losses as described in Text S3. Private flood insurance is not represented.

Capital and risk transfer

Private insurer capital is statutory surplus as regards policyholders for calendar year 2024, obtained from NAIC statutory financial statements through S&P Capital IQ. We record both entity and group surplus to

represent the intragroup support described in Text S4. Citizens' surplus comes from its 2024 annual statutory financial statement ([Citizens Property Insurance Corporation, 2024a](#)). The NFIP fund pool is the combined National Flood Insurance Fund and Reserve Fund balance of USD 3.441 billion as of October 28, 2024 ([Congressional Research Service, 2025](#)). Florida written premiums provide the denominator for the NFIP stress indicator.

FHCF inputs follow the 2023–2024 reimbursement contract. Company coverage elections of 45%, 75%, or 90%, reimbursement premiums, and NAIC identifiers come from FHCF coverage selections and premium calculation reports ([Florida Hurricane Catastrophe Fund, 2024b](#)). Retention multiples follow the 2023 ratemaking formula report. The payout multiple is the updated 2023 value reported in the 2024 ratemaking report ([Florida Hurricane Catastrophe Fund, 2023b, 2024a](#)). We impose a statewide seasonal reimbursement cap of USD 17 billion. The model includes FHCF recoveries and catastrophe bonds but does not represent other private reinsurance treaties.

The catastrophe bond input inventory records principal, sponsor, covered perils, trigger type, and issue date from the Artemis deal directory ([Artemis.bm, 2024](#)). We retain eight indemnity issues dated January–September 2024, totaling USD 2.54 billion in principal, whose reported coverage includes Florida and whose beneficiaries can be assigned to modeled insurers using statutory entity identifiers. We exclude issues without Florida coverage and those with unresolved allocations across insurance groups or multiple beneficiaries. Industry loss and parametric bonds are not represented. This selection does not cover the full stock of bonds outstanding in 2024. The inventory does not provide attachment or exhaustion points; these are prescribed as described in Text S4.

Text S2 Hurricane hazards and economic loss generation

Historical and synthetic tracks

Historical tropical cyclone (TC) tracks come from the International Best Track Archive for Climate Stewardship (IBTrACS) ([Knapp et al., 2010](#)). Synthetic tracks are generated with the statistical-dynamical TC model developed at the Massachusetts Institute of Technology (MIT) ([Emanuel et al., 2006, 2008](#)). We use environmental fields from ERA5, the fifth-generation atmospheric reanalysis from the European Centre for Medium-Range Weather Forecasts, for present-day conditions ([Hersbach et al., 2020](#)) and five global climate models (GCMs) from phase 6 of the Coupled Model Intercomparison Project (CMIP6) for the climate comparisons. These are CanESM5 ([Swart et al., 2019](#)), CNRM-CM6-1 ([Voldoire et al., 2019](#)), EC-Earth3 ([EC Earth Consortium, 2019](#)), IPSL-CM6A-LR ([Hourdin et al., 2020](#)), and MIROC6 ([Tatebe et al., 2019](#)).

The ERA5 reference covers 1980–2023. Each GCM provides a historical reference for 1995–2014 and future conditions for 2041–2060 and 2081–2100 under Shared Socioeconomic Pathway (SSP) scenarios SSP2–4.5 and SSP5–8.5. The model generates 200 TCs per year through genesis, track, and intensity simulations. This yields 8,800 TCs in the ERA5 set and 4,000 in each GCM, period, and scenario set before spatial filtering. We retain tracks passing within 150 km of the Florida coast.

Annual frequency is derived from the fraction of seeded disturbances that develop into storms with winds above 40 kn under the environmental conditions of each simulation. A frequency correction adjusts the number of developed storms relative to the seeded ensemble to match the calibrated climatological baseline. The resulting frequencies retain differences among the climate simulations and are used to sample the synthetic seasons in Text S5.

We note that Atlantic TC activity varies on decadal and longer timescales, so the historical reference period

influences the hazard baseline (Vecchi et al., 2021; Emanuel, 2021). Assumptions about TC frequency also affect modeled loss distributions (Liu et al., 2026). Our results are conditional on the 1980–2023 ERA5 baseline; we do not evaluate sensitivity to alternative historical reference periods.

Wind and flood contributions

The financial model treats wind and flood losses separately because they are covered by different insurance programs. We estimate their relative contributions using the multi-hazard regression developed by Gori et al. (2025). That study combines county-level wind, precipitation, and storm surge intensities from physical hazard models with a damage regression calibrated to observed losses. Its synthetic TCs are generated with the same underlying MIT track model used in our analysis. We use the relative contributions from the regression to divide the total economic losses calculated with the CLIMADA climate risk modeling platform (Aznar-Siguan & Bresch, 2019) into wind and flood components. We do not use the regression to recalculate total economic loss.

For event e and county c , the contributions in the regression are

$$c_{V,e,c} = \beta_V \ln V_{\max,e,c}, \quad c_{P,e,c} = \beta_P \ln(P_{\text{cum},e,c} + 1), \quad c_{S,e,c} = \beta_S S_{\max,e,c}, \quad (\text{S1})$$

where $V_{\max}$, P_{cum} , and $S_{\max}$ denote maximum wind speed, cumulative precipitation, and maximum surge. The coefficients follow the regional specification of Gori et al. (2025). Their sum defines the compound hazard intensity

$$H_{e,c} = c_{V,e,c} + c_{P,e,c} + c_{S,e,c}. \quad (\text{S2})$$

For each county, we select events at or above its 95th percentile of $H_{e,c}$. We then average their relative wind contributions

$$\tilde{r}_{V,c} = \left\langle \frac{c_{V,e,c}}{c_{V,e,c} + c_{P,e,c} + c_{S,e,c}} \right\rangle_{H_{e,c} \geq H_c^{(p95)}}. \quad (\text{S3})$$

This gives an average contribution of 84.6% from wind, 10.2% from storm surge, and 5.2% from precipitation. Storm surge and precipitation together define the flood contribution.

We sample a wind share for each event from a Beta distribution with shape parameters $m\kappa$ and $(1-m)\kappa$, where m is the mean and κ the concentration. Synthetic events use $m = 0.846$ and $\kappa = 10$. The historical means are 0.70 for Great Miami, 0.875 for Andrew, 0.30 for Lake Okeechobee, and 0.50 for Irma. Concentration is 10 except for Lake Okeechobee, where it is 8. These distributions express uncertainty in the assumed peril allocation. Constructed sequences have one combined wind share. Great Miami followed by Andrew uses $m = 0.76$ and $\kappa = 25$, while repeated Great Miami and Irma use their single storm means and $\kappa = 30$.

We proportionally rescale the county shares toward the sampled share. If w_e is the draw, the scaling factor is $w_e/\bar{r}_e$, where $\bar{r}_e = \sum_c L_{\text{total},e,c} \tilde{r}_{V,c} / \sum_c L_{\text{total},e,c}$. The resulting county shares are clipped to $[0, 1]$. Clipping can cause the attained statewide share to differ from w_e . The county wind and flood losses are

$$L_{V,e,c} = L_{\text{total},e,c} r_{V,e,c}, \quad L_{F,e,c} = L_{\text{total},e,c} (1 - r_{V,e,c}), \quad (\text{S4})$$

where $r_{V,e,c}$ is the rescaled county share. Flood loss is the residual after wind loss. In the financial equations below, $L_{W,c}$ denotes the same wind loss as $L_{V,e,c}$, with the event index omitted.

Text S3 Insured loss allocation

Empirical basis for the insured wind fraction

We estimate the fraction of Florida hurricane economic losses covered by insurance using data from FLOIR, NFIP payouts, and federal disaster assistance. The reconstruction follows the approach in the U.S. Billion-Dollar Weather and Climate Disaster Database (Smith & Katz, 2013; Smith & Matthews, 2015). With federal assistance included, estimated economic loss is

$$L_{\text{econ}} = 2 \cdot L_{\text{insured}} + L_{\text{NFIP}} + L_{\text{FDA}}, \quad (\text{S5})$$

where L_{insured} is FLOIR insured loss, L_{NFIP} is NFIP payouts, and L_{FDA} is federal disaster assistance. The factor of two accounts for uninsured private losses in this reconstruction (Smith & Katz, 2013). Because the treatment of assistance is uncertain, we also calculate economic losses excluding L_{FDA} . For each estimate, the insured fraction is

$$f_{\text{insured}} = \frac{L_{\text{insured}}}{L_{\text{econ}}}. \quad (\text{S6})$$

FLOIR loss reports cover hurricane losses in 2017–2020 and 2022–2024 (Florida Office of Insurance Regulation, 2026). NFIP payouts come from FEMA’s Floodsmart database (NFIP, 2026), and assistance from FEMA disaster summaries (Federal Emergency Management Agency (FEMA), 2026). We convert these monetary values to 2024 USD using the Consumer Price Index for All Urban Consumers (CPI-U) from the U.S. Bureau of Labor Statistics (US Bureau of Labor Statistics, 2026). Table S1 reports both estimates for each year. The annual shares range from 11.76% to 49.34% across the two formulations. Mean shares for years exceeding USD 25 billion in estimated economic loss are 40.68% with assistance included and 44.03% with assistance excluded.

The reconstructed shares motivate a Beta(4,6) distribution, with a mean of 0.40, for the fraction of wind loss assigned to insurance. The model independently samples a value from this distribution for each county and simulated season. This is an indirect calibration. The reconstructed fraction has total economic loss in its denominator, whereas the model applies it to wind loss. We therefore treat 0.40 as an allocation assumption and evaluate its influence in Text S6. It is not a direct estimate of the proportion of properties with wind insurance.

Allocation to insurance portfolios

For county c , the sampled fraction f_W divides economic wind loss into insured loss and a residual

$$L_{W,c}^{\text{ins}} = f_W L_{W,c}, \quad L_{W,c}^{\text{hh}} = (1 - f_W) L_{W,c}. \quad (\text{S7})$$

The residual does not enter insurers’ balance sheets. We allocate insured wind losses between private insurers and Citizens according to their county TIV shares. The private share is then distributed among insurers i

$$G_i = \sum_c \frac{v_{i,c}}{V_c^{\text{priv}}} \sigma_c L_{W,c}^{\text{ins}}, \quad G_{\text{Cit}} = \sum_c (1 - \sigma_c) L_{W,c}^{\text{ins}}, \quad (\text{S8})$$

where $v_{i,c}$ is insurer i ’s county TIV, $V_c^{\text{priv}} = \sum_i v_{i,c}$, and σ_c is the private market share of insured wind value in that county. Thus G_i and G_{Cit} are gross insured wind losses before recoveries.

FEMA defines residential penetration as insured residential structures divided by the estimated number of residential structures, using the 2022 National Structure Inventory for the denominator (Federal Emergency

[Management Agency \(FEMA\), 2025](#)). We use the county rate $r_{\text{all},c}$, the SFHA rate $r_{\text{SFHA},c}$, and the counts of all and SFHA residential structures. The SFHA fraction is $s_c = n_{\text{SFHA},c}/n_{\text{all},c}$, constrained to zero through one. We infer the non-SFHA rate as $(r_{\text{all},c} - s_c r_{\text{SFHA},c})/(1 - s_c)$ and constrain it to the same range. Missing and undefined rates are set to zero. The effective county rate is $\tau_c = s_c r_{\text{SFHA},c} + (1 - s_c) r_{\text{non},c}$.

We assume that the share of residential structures insured also represents the fraction of county flood loss insured. The county allocation is capped by aggregate coverage in force CIF_c

$$L_{F,c}^{\text{ins}} = \min(\tau_c L_{F,c}, \text{CIF}_c), \quad L_{F,c}^{\text{hh}} = L_{F,c} - L_{F,c}^{\text{ins}}. \quad (\text{S9})$$

All insured flood loss is assigned to the NFIP. Federal disaster assistance is used only in the empirical reconstruction above and not in this flood allocation.

The notation L^{hh} denotes the combined uninsured wind and flood residuals. We report their sum as uninsured losses. The exposure and vulnerability inputs do not distinguish residential from nonresidential economic losses. The residual therefore cannot be attributed entirely to households. Its magnitude depends on the allocation of aggregate economic losses to the residential insurance system.

Text S4 Institutional risk propagation

We apply recoveries, capital, and institutional financing to the gross losses defined in Text S3. The calculation runs once for an individual event or for the combined county losses of a constructed sequence or synthetic season. Each season starts from the same capital positions. For readability, the event or season index is omitted from the equations below.

FHCF recoveries

For insurer i , gross insured wind loss is summed across all counties before applying the company's retention and limit. The reimbursement premium Π_i and coverage election $p_i \in \{0.45, 0.75, 0.90\}$ determine retention R_i and company limit K_i

$$R_i = m_{\text{ret}}(p_i) \Pi_i, \quad K_i = m_{\text{pay}} \Pi_i. \quad (\text{S10})$$

The retention multiples are $m_{\text{ret}}(0.90) = 6.0732$, $m_{\text{ret}}(0.75) = 7.2878$, and $m_{\text{ret}}(0.45) = 12.1464$. The payout multiple is $m_{\text{pay}} = 11.2368$ ([Florida Hurricane Catastrophe Fund, 2023b, 2024a](#)). Following the 2023–2024 reimbursement contract, the company limit caps reimbursement after applying the coverage election and the 10% loss adjustment expense allowance ([Florida Hurricane Catastrophe Fund, 2023a](#))

$$\text{Rec}_i = \min\left(\lambda p_i \max(G_i - R_i, 0), K_i\right), \quad \lambda = 1.10. \quad (\text{S11})$$

This recovery is calculated once per company and allocated back to its counties in proportion to their gross insured wind losses. A company with zero gross loss receives zero recovery. Splitting a company's loss among more counties therefore does not repeat its retention or limit.

The contract defines loss and retention by company and covered event. We retain a seasonal approximation that applies equation (S11) once to the company's combined seasonal loss. We do not reproduce event ordering, repeated retentions, or contract adjustments for multiple events within the season. Citizens is represented as one company rather than separate statutory accounts.

Combined recoveries across private insurers and Citizens cannot exceed $C_{\text{FHCF}} = \$17$ billion. If $A = \sum_i \text{Rec}_i$, the final recovery is

$$\widetilde{\text{Rec}}_i = \text{Rec}_i \min\left(1, \frac{C_{\text{FHCF}}}{A}\right), \quad (\text{S12})$$

with zero recoveries when $A = 0$. The statewide shortfall is $F_{\text{FHCF}} = \max(A - C_{\text{FHCF}}, 0)$. Utilization is $\sum_i \widetilde{\text{Rec}}_i / C_{\text{FHCF}}$. These are distinct outputs. Company limits in the supplied premium snapshot sum to less than the statewide capacity. The statewide cap therefore cannot bind for this portfolio, although individual companies can exhaust their limits. We retain the cap and report FHCF recoveries separately from downstream residual requirements.

The loss remaining with insurer i is $N_i^{\text{F}} = G_i - \widetilde{\text{Rec}}_i$. Company premiums and elections remain fixed. The contract year does not imply that every financial input shares the same reporting date (Text S1).

Catastrophe bonds

For each included bond b , let P_b be its reported principal and $i(b)$ its modeled beneficiary. We set the attachment and maximum payout equal to P_b , giving the stylized recovery

$$\widehat{B}_b = \min\left(\max(N_{i(b)}^{\text{F}} - P_b, 0), P_b\right). \quad (\text{S13})$$

Here, N_i^{F} is the insurer's retained wind loss after FHCF reimbursement. Recovery begins above P_b and reaches its maximum at a loss of $2P_b$. These layer terms are assumed because transaction-specific attachment and exhaustion points are unavailable in the input inventory.

Total credited recovery for insurer i is $B_i = \min(N_i^{\text{F}}, \sum_{b:i(b)=i} \widehat{B}_b)$, leaving $N_i = N_i^{\text{F}} - B_i$ to be deducted from capital. Recoveries are allocated across the beneficiary's counties in proportion to retained wind losses. A beneficiary with no wind losses receives zero recovery. Bond payouts do not change FHCF reimbursements.

Each layer is applied once to the aggregate loss used in the event or seasonal analysis, without reinstatement. The calculation does not resolve occurrence-specific contract terms, other covered perils, losses outside Florida, or individual tranches within an issuance.

Capital depletion and group support

We deduct net loss from statutory surplus S_i , leaving $E_i = S_i - N_i$. An entity with $E_i < 0$ is provisionally insolvent. We then consider support within groups defined by NAIC parent identifiers. Support is available only when the ratio of group surplus to the distressed entity's initial surplus exceeds 10.

For group g , the available pool combines surplus held outside its modeled entities and positive post-loss surplus within those entities

$$P_g = \max\left(S_g^{\text{grp}} - \sum_{i \in g} S_i, 0\right) + \sum_{i \in g} \max(E_i, 0). \quad (\text{S14})$$

We draw first on the parent pool and then on solvent members in proportion to their remaining surplus. Contributions do not push a supporting entity below zero. Eligible deficits can be covered only up to the available pool. If $C_i \geq 0$ is the contribution to entity i , its adjusted surplus is $E_i' = E_i + C_i$. Before default classification, adjusted balances with absolute values below USD 0.01 are set to zero to remove numerical roundoff. An entity defaults when its resulting balance is negative; a deficit of exactly USD 0.01 is retained. The support rule is an assumption, not an observed commitment by the parent company.

Florida Insurance Guaranty Association assessments

The Florida Insurance Guaranty Association (FIGA) receives the aggregate deficit of defaulted private insurers, $D_{\text{FIGA}} = \sum_{i: E'_i < 0} (-E'_i)$. We represent assessment capacity as 2% normal plus 4% emergency assessments on surviving insurers' written premiums Π_{surv} . The residual is

$$F_{\text{FIGA}} = \max(D_{\text{FIGA}} - 0.06\Pi_{\text{surv}}, 0). \quad (\text{S15})$$

Assessments meet part of the deficit. Residual FIGA deficits below USD 0.01 are likewise treated as zero in the reported outcomes. The residual identifies the requirement beyond this modeled capacity, without assigning it to a final payer. The calculation does not simulate subsequent collections or financing backed by future assessments.

Citizens assessments

Citizens' gross wind loss passes through the same risk transfer steps, leaving net loss N_{Cit} . Its deficit after surplus is $D_{\text{Cit}} = \max(N_{\text{Cit}} - S_{\text{Cit}}, 0)$. We represent Citizens' policyholder surcharge and emergency assessment through two financing tiers, based on the assessment mechanisms described by Citizens and in Florida Statutes ([Citizens Property Insurance Corporation, n.d.](#); [State of Florida, 2024](#)). In the model, the first tier is limited to 15% of Citizens' premium base Π_{Cit} , and the second to 10% of the modeled statewide property premium base Π_{state}

$$T_1 = \min(D_{\text{Cit}}, 0.15\Pi_{\text{Cit}}), \quad (\text{S16})$$

$$T_2 = \min(D_{\text{Cit}} - T_1, 0.10\Pi_{\text{state}}), \quad (\text{S17})$$

$$F_{\text{Cit}} = \max(D_{\text{Cit}} - T_1 - T_2, 0). \quad (\text{S18})$$

The residual F_{Cit} remains after both modeled tiers. Citizens' accounts and assessment mechanisms are represented by this combined calculation. The model does not simulate borrowing against future assessment streams.

NFIP financing

NFIP payouts first draw on the national fund pool $P_{\text{NFIP}} = \$3.441$ billion. The requirement beyond this pool is

$$\text{NFIP}_{\text{borrow}} = \max\left(\sum_c L_{F,c}^{\text{ins}} - P_{\text{NFIP}}, 0\right). \quad (\text{S19})$$

We describe this as an NFIP financing requirement. The calculation applies the national fund balance to Florida claims without competing claims from other states. It includes neither NFIP reinsurance nor a limit on additional Treasury borrowing. The result can therefore exceed currently available borrowing authority. It does not determine the eventual fiscal cost of meeting that requirement.

Residual financing requirement

For season s , we sum the three downstream requirements

$$R_s = F_{\text{FIGA},s} + F_{\text{Cit},s} + \text{NFIP}_{\text{borrow},s}. \quad (\text{S20})$$

FHCF shortfall is reported separately. Any unrecovered FHCF claim either reduces remaining insurer capital or contributes to a downstream deficit. Including it again in equation (S20) would count that portion twice

where it reaches FIGA or Citizens. FHCF reimbursements are also reported separately because they are a recovery paid before those residuals arise.

The three components describe financing needs after different resources have been exhausted. Assessments paid within the modeled capacity distribute costs among insurers and policyholders. The remaining FIGA and Citizens deficits have no assigned final payer. The NFIP component represents demand for federal financing under the stated assumptions. Their sum does not identify the eventual distribution of losses among claimants, policyholders, taxpayers, or other parties.

Text S5 Scenario design and analysis

Historical and sequential stress tests

We apply the model to the 1926 Great Miami Hurricane, 1992 Hurricane Andrew, 1928 Lake Okeechobee Hurricane, and 2017 Hurricane Irma. We also construct Great Miami followed by Andrew, Great Miami twice, and Irma twice. Each historical or paired scenario has 1,000 parameter realizations with fixed storm tracks. These footprints are evaluated under the study's exposure and financial inputs rather than the markets in the years when the storms occurred.

For paired storms, losses are computed sequentially to account for reductions in exposed asset values after the first event. We do not model potential changes in vulnerability between events due to limited empirical evidence. These sequential scenarios should therefore be interpreted as stylized stress tests that capture exposure depletion but do not incorporate increased vulnerability from prior damage or physical recovery between events. For each storm pair, the resulting county losses are summed before the financial calculation is applied once. For synthetic seasons, county wind and flood losses are likewise summed across events before one financial calculation. Capital, group support, recoveries, and institutional resources are evaluated against these aggregate losses. Financial recovery between storms and market recovery across successive seasons are outside the model.

Synthetic seasons and outcome metrics

For each hazard set, we sample events with replacement according to its annual TC frequencies to construct 10,000 synthetic seasons. We retain all simulated seasons in means, exceedance probabilities, and return levels.

Each realization samples the insured wind fraction, the event wind shares, and company exposure within counties. Other market inputs and institutional parameters remain fixed unless explicitly varied in a scenario analysis. We record economic losses, insurance allocation, insurer defaults, the largest entity deficit, institutional capacity exceedances, and the residual financing requirement. Table S2 defines the outputs and thresholds.

For a condition $\mathcal{B}$, annual exceedance probability is

$$P(\mathcal{B}) = \frac{1}{N} \sum_{s=1}^N \mathbf{1}[\mathcal{B}_s], \quad N = 10,000. \quad (\text{S21})$$

The indicators include more than ten private defaults, an entity deficit above USD 1 billion, positive residual deficits after FIGA or Citizens assessment capacity, NFIP claims above twice Florida NFIP annual premiums, and residual financing requirements above 1% or 10% of Florida gross domestic product (GDP). FHCF ca-

capacity exceedance requires positive statewide reimbursement shortfall. This does not occur for the supplied portfolio (Text S4).

Seasonal return periods use the synthetic year sets. Event return periods use annual frequencies of individual storms. Figure S1 compares the corresponding economic loss curves.

Systemic risk under future climate conditions

To assess systemic risk under future climate conditions, we focus on SSP2–4.5. Tables S4 and S5 also report SSP5–8.5. Both pathways use the same five GCMs, historical reference, future periods, and financial model. Exposure, market shares, capital, and institutional rules remain at their study values. These analyses describe the response of the present market configuration to changing hurricane hazard.

Let $M_{g,h}$ and $M_{g,f}$ denote a metric from GCM g for its historical and future periods. Its change is $\Delta_g = M_{g,f} - M_{g,h}$. We estimate the future value relative to the ERA5 baseline as

$$\hat{M}_f = M_{\text{ERA5}} + \text{median}_g(\Delta_g). \quad (\text{S22})$$

The spread is $M_{\text{ERA5}} + [Q_{0.10}(\Delta_g), Q_{0.90}(\Delta_g)]$. We estimate future risk by adding GCM-derived climate change deltas to the ERA5-based baseline. This retains the reanalysis-based estimate of present-day risk while incorporating the changes projected by the GCMs. It avoids carrying differences in baseline risk between the GCM- and ERA5-driven simulations directly into the future estimates. Such differences can arise from the large-scale environmental conditions used for downscaling (Emanuel et al., 2008). Biases in the projected changes themselves can remain.

For monetary outcomes and the number of insurer defaults, M is the average across simulated seasons. For threshold indicators, M is the fraction of seasons in which the threshold is exceeded. We calculate each metric separately for the historical and future simulations of each GCM, then add the median change across GCMs to the corresponding ERA5 baseline. Changes in exceedance probabilities are added in percentage points.

The 10th–90th percentile range describes variation in projected changes across the five GCMs. It does not include sampling uncertainty in the ERA5 baseline, which is estimated separately by bootstrapping.

Stylized market and policy analyses

We assess three stylized market and policy scenarios under present hazard conditions, using 10,000 seasons per analysis. Each scenario modifies selected components of the insurance system while retaining the remaining baseline assumptions.

Private insurer market exit. We model a contraction of the private insurance market that raises Citizens’ target share from 15% to 25% of total insured value. Of the insured value leaving private insurers, 85% transfers to Citizens and 15% is removed from the portfolio inputs. These changes redistribute insured wind losses between private insurers and Citizens while leaving the aggregate insured wind fraction, initial insurer surplus, and premium inputs unchanged. Removing portfolio value therefore changes the allocation of insured losses without increasing aggregate uninsured losses. Gross wind and flood losses remain unchanged.

Insurance penetration increase. We model expanded insurance coverage together with depopulation of Citizens. The assumed insured wind fraction increases from 40% to 60%, and the target NFIP participation rate increases from approximately 11% to 30%. County flood participation rates derived from FEMA data (Federal Emergency Management Agency (FEMA), 2025) are multiplied by the ratio of target to baseline participation

and capped at 98%. The 30% value denotes the scenario target rather than a measured statewide rate after these adjustments. Citizens' target share decreases from 15% to 8% through transfers to private insurers. Wind insurance portfolios expand more strongly in coastal than inland counties, and insurer surplus and premium bases adjust proportionally with exposure growth. Gross wind and flood losses remain unchanged.

Building code improvement. We model the potential effects of stronger building standards and retrofitting through stylized reductions of 30% in wind losses and 25% in flood losses. These reductions are applied before losses are allocated into insured and uninsured components. Exposure values and insurer capital remain unchanged. The scenario represents physical damage reduction without modeling specific engineering measures or their implementation costs.

Loss reductions needed to offset climate effects

We assess how much prescribed loss reduction is needed to offset the mid-century SSP2–4.5 effects on mean economic loss, the mean number of private insurer defaults, and the mean residual financing requirement. Each GCM supplies 10,000 historical seasons for 1995–2014 and 10,000 future seasons for 2041–2060. We apply 13 wind and flood reduction pairs to the future losses. In percent, these are

$$\begin{aligned} (r_W, r_F) \in \{ & (0, 0), (20, 13), (30, 20), (40, 27), (50, 33), \\ & (60, 40), (70, 47), (80, 53), (90, 60), \\ & (100, 67), (100, 70), (100, 80), (100, 90) \}. \end{aligned} \quad (\text{S23})$$

These percentages reduce the wind and flood losses before they enter the insurance calculation. The first part of the sequence approximates a 3 to 2 ratio. Once the wind reduction reaches 100%, only the flood reduction increases. The sequence therefore has no single constant ratio or common percentage reduction.

For each pair, we subtract the corresponding GCM historical mean from the future mean after loss reduction and then apply equation (S22). Figure S2 shows the median response and the 10th–90th percentile GCM range. An offset is reached when the median future result falls to or below the ERA5 baseline. We interpolate linearly between the adjacent tested pairs that bracket this crossing and report the resulting wind and flood reductions. If no tested pair brackets a crossing, we do not extrapolate beyond the tested range.

Text S6 Statistical analysis and uncertainty

Return levels and amplification

For each simulated season s , we calculate the total residual financing requirement R_s by summing the institutional components in equation (S20). The return level associated with a return period of T years is the value exceeded with annual probability $1/T$, estimated as

$$q_R(T) = Q_{1-1/T}(R_1, \dots, R_N), \quad (\text{S24})$$

where Q_p denotes the empirical quantile at probability p and $N = 10,000$ is the number of simulated seasons. We include all seasons, including those with no residual financing requirement, and estimate quantiles by linear interpolation between sorted values. Return levels for individual institutional components are calculated separately and are not summed to obtain $q_R(T)$.

We calculate return levels for total economic loss, $q_L(T)$, in the same way. Comparing $q_L(T)$ and $q_R(T)$ at a common return period shows how economic losses and financing requirements increase toward rarer

outcomes. These return levels are estimated from their respective distributions and need not correspond to the same simulated seasons.

To quantify amplification, we calculate the ratio of the 100-year to the 10-year return level separately for economic losses and residual financing requirements. We also fit a power law relating $q_R(T)$ to $q_L(T)$ across return periods of 10, 25, 50, 100, 250, 500, and 1,000 years, using ordinary least squares on their logarithms. The fitted exponent describes how rapidly financing return levels increase relative to economic loss return levels. It does not measure the effect of an additional dollar of loss within an individual season. The return levels are reported in Table 1 of the main manuscript, and their relationship is shown in Figure 3.

To examine how institutional financing needs vary with loss severity, we group simulated seasons by total economic loss using boundaries of USD 39.5, 147, 246, 357, and 564 billion, which approximate the baseline 10-, 25-, 50-, 100-, and 250-year return levels. Seasons with losses up to USD 1 form a separate group. Positive-loss groups containing fewer than 50 seasons are merged into the next lower occupied group until this minimum is reached, except for the lowest occupied positive-loss group.

Within each group, we calculate the mean FIGA residual deficit, Citizens residual deficit, and NFIP financing requirement, including seasons in which a component is zero. These means sum to the group's mean residual financing requirement. Table S8 reports group means and sample sizes, and Figure S4 expresses each component mean as a share of mean economic loss within the same group. This decomposition describes institutional contributions to financing needs without isolating the effects of individual capacities or thresholds.

Sampled parameters and sampling uncertainty

We sample the insured wind fraction from a Beta(4,6) distribution, as described in Text S3. In the insurance penetration increase scenario, this fraction is instead fixed at 60% (Text S5). Fixed fractions are also used in the sensitivity analysis described below. Wind share distributions are given in Text S2. For each insurer and county, we sample total insured value from a normal distribution centered on the input value, with a standard deviation of 15% of that value. Negative draws are set to zero. These draws vary between realizations and affect the allocation of insured losses. Statutory surplus is not sampled. Table S7 distinguishes sampled inputs, fixed assumptions, and climate ensemble variation.

We estimate sampling uncertainty in return levels and annual exceedance probabilities using 1,000 bootstrap resamples of the 10,000 simulated seasons. Each resample draws complete seasons with replacement, keeping economic losses and financial outcomes from the same season together. We recalculate each metric and report the 10th–90th percentiles of the bootstrap estimates. This procedure applies to the ERA5 baseline and the three stylized market and policy scenarios described in Text S5. For the percentage-point changes shown in Figure 4b of the main manuscript, we resample matched baseline and scenario seasons together before calculating the probability difference.

Sensitivity to the insured wind fraction

We run the model at fixed insured wind fractions from 0.1 to 0.5 in steps of 0.1, with 10,000 seasons for each value. Table S6 reports mean outcomes, changes relative to 0.4, and local log–log elasticities near 0.4. We estimate the latter as $[\ln M(0.5) - \ln M(0.3)] / [\ln(0.5) - \ln(0.3)]$, where $M(f)$ is the unrounded mean at fixed insured fraction f . A value near one indicates proportional response. A value above one indicates a more than proportional response near the reference fraction. An elasticity is undefined for a quantity that remains zero throughout the sweep.

This sensitivity analysis measures the effect of allocating more wind loss to insurance while preserving the other assumptions. It does not validate the allocation fraction or test insurer geography, omitted reinsurance, or other fixed institutional rules. We retain the baseline NFIP allocation in this sweep. Its use of residential structure shares as loss shares remains an uncertainty, rather than a separately quantified financial sensitivity.

Supporting tables

Table S1: **Insured and estimated economic losses and resulting insured shares for Florida hurricane events (2017–2024)**. Economic losses are estimated using formulations including and excluding federal disaster assistance (FDA). All values are converted to 2024 USD.

Year	Insured losses	Est econ loss (incl. FDA)	f_{insured} (incl.)	Est econ loss (excl. FDA)	f_{insured} (excl.)
2017	28,159,458,046	60,750,223,673	46.35%	57,644,860,280	48.85%
2018	11,472,501,417	26,081,530,262	43.99%	23,251,364,093	49.34%
2019	23,342,615	198,468,914	11.76%	80,793,892	28.89%
2020	699,057,474	2,041,794,621	34.24%	1,783,712,209	39.19%
2021	n.a.	n.a.	n.a.	n.a.	n.a.
2022	23,914,182,689	56,175,193,964	42.57%	53,075,926,756	45.06%
2023	318,470,377	1,754,055,340	18.16%	1,315,565,662	24.21%
2024	7,466,073,319	25,060,543,556	29.79%	22,700,454,161	32.89%
Mean			32.41%		38.35%
Median			34.24%		39.19%
High-loss mean (> \$25B)			40.68%		44.03%

Table S2: Definitions of systemic risk metrics used in the main text and Supporting Information. Text S4 defines the financial components and their aggregate. Ratio summaries exclude realizations with a zero denominator. Capacity exceedance probabilities use the stated indicators directly.

Metric	Unit	Definition
<i>Loss allocation</i>		
Total loss	USD	Aggregate economic TC loss before allocation to insurance portfolios.
Insured wind, private	USD	Wind loss assigned to private insurers before recoveries.
Citizens wind	USD	Wind loss assigned to Citizens before recoveries.
Insured flood, NFIP	USD	Flood loss assigned to the NFIP, subject to county coverage limits.
Uninsured wind	USD	Wind loss remaining outside private and Citizens insurance.
Uninsured flood	USD	Flood loss remaining outside NFIP coverage.
Total uninsured loss	USD	Sum of uninsured wind and flood residuals. Aggregate economic exposure prevents attribution entirely to households.
Insured or uninsured share	%	Share of total economic loss assigned to insurance or left uninsured.
<i>Institutional outcomes</i>		
FHCF reimbursement	USD	Combined reimbursement to private insurers and Citizens after company limits and the statewide cap.
FHCF shortfall	USD	Company reimbursement demand above the USD 17 billion statewide cap. It is separate from the residual financing requirement.
FIGA residual deficit	USD	Insolvency deficit remaining after modeled FIGA assessment capacity.
Citizens residual deficit	USD	Deficit remaining after recoveries, Citizens' surplus, and both assessment tiers.
NFIP financing requirement	USD	Florida NFIP claims above the national fund balance, without NFIP reinsurance or a borrowing limit.
Residual financing requirement	USD	Sum of FIGA and Citizens residual deficits and NFIP financing requirements within each season.
<i>Capital depletion and defaults</i>		
Private defaults	count	Private insurer entities with negative surplus after losses, recoveries, and group support.
Largest entity deficit	USD	Largest remaining capital shortfall among insurer entities in a realization.
<i>Institutional ratios</i>		
FHCF utilization	ratio	Total FHCF reimbursement divided by USD 17 billion.
Citizens residual assessment ratio	ratio	Citizens' residual deficit after assessments divided by the combined capacity of both assessment tiers.
FIGA unfunded share	ratio	FIGA residual deficit divided by the sum of that residual and assessments collected. Undefined if both are zero.
NFIP Florida claims ratio	ratio	Florida NFIP claims paid divided by Florida NFIP annual premiums.
<i>Annual exceedance indicators</i>		
Defaults > 10	annual probability (%)	More than ten private insurer defaults in a simulated season.
Largest deficit > \$1B	annual probability (%)	Largest entity deficit exceeds USD 1 billion.
FHCF reimbursement shortfall	annual probability (%)	Positive statewide FHCF shortfall. This is zero for the supplied portfolio and omitted from the outcome displays.
FIGA capacity exceeded	annual probability (%)	Positive FIGA residual deficit after modeled assessments.
Citizens capacity exceeded	annual probability (%)	Positive Citizens residual deficit after both assessment tiers.
NFIP claims > 2 times premiums	annual probability (%)	Florida NFIP claims exceed twice Florida NFIP annual premiums.
Residual financing requirement > 1% Florida GDP	annual probability (%)	The seasonal three component sum exceeds 1% of Florida GDP.
Residual financing requirement > 10% Florida GDP	annual probability (%)	The seasonal three component sum exceeds 10% of Florida GDP.

Table S3: Historical and sequential hurricane stress tests. Values are means with the 5th to 95th percentile across 1,000 parameter realizations in parentheses. Monetary quantities are in billion USD. Historical footprints are evaluated under the study's exposure and market assumptions. The residual financing requirement is the sum of FIGA and Citizens residual deficits and NFIP financing requirements within each realization. FHCF utilization describes reimbursement relative to statewide capacity. FIGA unfunded share is residual deficit divided by residual deficit plus collected assessments, conditional on a positive denominator. Citizens residual-to-capacity ratio divides its residual deficit by modeled assessment capacity. Neither ratio defines the binary exhaustion indicator, which is based on a positive residual deficit.

Metric (USD B, counts or ratios)	Great Miami	Andrew	Lake Okeechobee	Irma	Great Miami then Andrew	Double Great Miami	Double Irma
Total loss	170.4 (170.4–170.4)	114.2 (114.2–114.2)	156.9 (156.9–156.9)	32.0 (32.0–32.0)	266.5 (266.5–266.5)	321.1 (321.1–321.1)	62.4 (62.4–62.4)
Insured wind, private	36.9 (20.2–56.1)	29.0 (14.0–46.4)	16.3 (4.3–31.6)	6.0 (2.8–9.5)	61.4 (35.6–90.6)	69.3 (42.7–98.1)	11.5 (7.4–15.9)
Citizens wind	10.3 (4.9–17.1)	10.3 (4.6–17.7)	2.6 (0.7–5.1)	0.5 (0.2–0.7)	18.8 (9.7–30.0)	19.4 (10.5–30.5)	0.9 (0.6–1.2)
Insured flood, NFIP	15.0 (4.9–27.7)	4.9 (0.5–12.9)	17.0 (10.5–22.4)	2.6 (1.3–4.0)	19.8 (9.4–31.9)	28.1 (16.1–41.4)	5.2 (3.6–6.7)
Un/underinsured wind	72.2 (42.5–101.3)	60.5 (37.8–84.5)	28.3 (7.6–55.4)	9.7 (4.7–14.9)	122.9 (84.4–165.0)	136.7 (96.0–180.5)	18.7 (12.8–25.5)
Un/underinsured flood	35.9 (11.4–66.8)	9.4 (0.9–24.7)	92.6 (57.3–121.9)	13.3 (6.5–20.1)	43.7 (20.5–70.7)	67.7 (38.5–100.1)	26.1 (18.0–33.8)
Residual financing requirement	22.4 (11.8–32.3)	10.4 (1.5–21.7)	15.0 (11.4–18.9)	0.2 (0.0–0.5)	45.4 (26.2–65.9)	57.6 (39.0–77.0)	2.2 (1.0–3.5)
FIGA residual deficit	6.8 (1.0–14.5)	4.1 (0.5–10.4)	1.1 (0.0–4.4)	0.1 (0.0–0.3)	16.8 (6.0–29.0)	20.1 (8.8–32.4)	0.4 (0.2–0.6)
Citizens residual deficit	4.1 (0.5–10.5)	4.1 (0.5–11.1)	0.3 (0.0–0.5)	0.0 (0.0–0.0)	12.2 (3.1–23.4)	12.8 (3.9–24.0)	0.1 (0.0–0.2)
NFIP financing requirement	11.5 (1.4–24.3)	2.2 (0.0–9.4)	13.6 (7.1–18.9)	0.1 (0.0–0.5)	16.4 (6.0–28.5)	24.7 (12.7–38.0)	1.8 (0.2–3.3)
Private defaults	17.6 (13.0–22.0)	15.6 (10.0–20.0)	11.0 (3.0–17.0)	5.2 (0.0–9.0)	21.3 (18.0–23.0)	22.0 (19.0–23.0)	9.6 (7.0–12.0)
Largest single-entity deficit	1.9 (0.3–3.8)	1.2 (0.3–2.9)	0.4 (0.0–1.3)	0.2 (0.0–0.3)	4.1 (1.6–7.1)	4.8 (2.3–7.8)	0.3 (0.3–0.3)
FHCF utilization factor	0.86 (0.69–0.89)	0.81 (0.50–0.89)	0.40 (0.01–0.77)	0.05 (0.00–0.17)	0.89 (0.89–0.89)	0.89 (0.89–0.89)	0.26 (0.08–0.44)
Citizens assessment stress factor	4.50 (0.55–11.69)	4.55 (0.54–12.32)	0.37 (0.00–0.55)	0.00 (0.00–0.00)	13.60 (3.45–26.03)	14.22 (4.33–26.63)	0.07 (0.00–0.22)
FIGA unfunded share	0.92 (0.73–0.98)	0.85 (0.54–0.97)	0.59 (0.00–0.93)	0.15 (0.00–0.46)	0.98 (0.95–0.99)	0.98 (0.97–0.99)	0.49 (0.30–0.60)
NFIP Florida stress factor	10.73 (3.49–19.86)	3.54 (0.35–9.23)	12.19 (7.56–16.02)	1.90 (0.95–2.85)	14.20 (6.74–22.89)	20.13 (11.54–29.68)	3.71 (2.58–4.79)

Table S4: Economic losses and financing requirements under climate and policy scenarios. All monetary values are in billion USD. Baseline and policy columns report seasonal means with the 10th to 90th percentile of seasonal outcomes in parentheses. Those ranges describe season-to-season variation and are not confidence intervals on the mean. Climate columns add the median and 10th to 90th percentile of five GCM future-minus-historical mean changes to the ERA5 mean. Aggregates are formed within each season before the climate adjustment. Climate adjustments are calculated separately for each component and for the total financing requirement. Because the median of a sum need not equal the sum of the medians, adjusted component means may not sum exactly to the adjusted total. Each probabilistic run contains 10,000 seasons. The 2050 and 2100 labels denote 2041–2060 and 2081–2100.

Metric (USD B)	Baseline	2050 SSP2-4.5	2050 SSP5-8.5	2100 SSP2-4.5	2100 SSP5-8.5	Market exit	Insurance penetration	Building codes
Total loss	19.3 (0.0–39.5)	48.5 (23.6–70.3)	54.1 (27.2–85.9)	64.9 (28.3–77.5)	91.8 (34.1–161.3)	19.3 (0.0–39.5)	19.3 (0.0–39.5)	13.7 (0.0–27.9)
Insured wind, private	5.5 (0.0–11.6)	13.9 (6.7–19.9)	15.4 (7.8–24.3)	18.5 (8.1–22.1)	26.2 (9.8–46.0)	4.7 (0.0–9.8)	8.1 (0.0–17.3)	3.8 (0.0–8.1)
Citizens wind	1.1 (0.0–1.8)	2.6 (1.3–3.8)	2.9 (1.5–4.6)	3.4 (1.5–4.1)	4.7 (1.8–8.6)	1.9 (0.0–3.5)	1.7 (0.0–2.8)	0.8 (0.0–1.2)
Insured flood, NFIP	0.6 (0.0–0.9)	1.5 (0.8–2.3)	1.7 (0.8–2.7)	1.9 (0.9–2.3)	2.7 (1.0–5.0)	0.6 (0.0–0.9)	1.7 (0.0–2.4)	0.5 (0.0–0.7)
Un/underinsured wind	9.7 (0.0–19.8)	24.3 (11.8–35.5)	27.5 (13.7–43.4)	32.9 (14.3–39.4)	46.6 (17.1–81.7)	9.7 (0.0–19.8)	6.5 (0.0–13.4)	6.8 (0.0–13.8)
Un/underinsured flood	2.4 (0.0–3.9)	6.2 (2.9–8.8)	6.6 (3.4–10.8)	8.2 (3.5–9.6)	11.5 (4.3–20.1)	2.4 (0.0–3.9)	1.3 (0.0–2.0)	1.8 (0.0–2.9)
Residual financing requirement	2.1 (0.0–0.7)	5.5 (2.6–8.6)	6.0 (3.1–10.8)	7.2 (3.1–9.5)	11.5 (3.9–23.3)	2.4 (0.0–0.9)	4.2 (0.0–0.9)	1.2 (0.0–0.4)
FIGA residual deficit	1.2 (0.0–0.4)	3.3 (1.5–5.1)	3.6 (1.9–6.5)	4.5 (1.9–5.9)	7.1 (2.4–14.2)	1.0 (0.0–0.4)	2.0 (0.0–0.0)	0.7 (0.0–0.3)
Citizens residual deficit	0.5 (0.0–0.2)	1.3 (0.6–2.2)	1.5 (0.7–2.7)	1.7 (0.8–2.3)	2.7 (1.0–5.7)	1.1 (0.0–0.5)	1.0 (0.0–0.4)	0.3 (0.0–0.2)
NFIP financing requirement	0.3 (0.0–0.0)	0.8 (0.4–1.4)	0.9 (0.5–1.7)	1.0 (0.4–1.4)	1.7 (0.6–3.4)	0.3 (0.0–0.0)	1.2 (0.0–0.0)	0.2 (0.0–0.0)

Table S5: **Annual probabilities of systemic insurance stress.** Values are percentages. Baseline and policy probabilities are the fractions of 10,000 seasons exceeding each threshold, with 10th to 90th percentile intervals from 1,000 whole-season bootstrap resamples. Climate estimates add the median change in each indicator probability across five GCMs to its ERA5 probability; parentheses show the corresponding GCM 10th to 90th percentile range. Probabilities are calculated directly from threshold indicators. Positive FIGA or Citizens residual deficit indicates exhaustion of the modeled assessment capacity.

Metric (%)	Baseline	2050 SSP2-4.5	2050 SSP5-8.5	2100 SSP2-4.5	2100 SSP5-8.5	Market exit	Insurance penetration	Building codes
Defaults > 10	8.71 (8.34–9.06)	21.09 (10.67–29.67)	24.90 (11.42–34.50)	28.62 (12.38–31.37)	35.12 (14.58–52.44)	7.86 (7.51–8.19)	7.83 (7.49–8.16)	6.83 (6.52–7.15)
Single deficit > \$1B	5.61 (5.31–5.91)	14.44 (6.78–19.92)	16.02 (7.40–23.74)	19.53 (7.97–21.44)	24.68 (9.34–40.09)	4.93 (4.67–5.21)	7.00 (6.70–7.34)	4.13 (3.89–4.39)
FIGA residual deficit > 0	13.65 (13.23–14.08)	32.24 (17.00–42.21)	36.33 (18.20–48.32)	41.23 (19.03–44.74)	50.79 (22.07–66.33)	12.61 (12.20–13.03)	9.02 (8.66–9.37)	11.54 (11.12–11.93)
Citizens residual deficit > 0	13.64 (13.21–14.09)	31.27 (16.49–39.93)	34.66 (17.52–45.58)	40.64 (18.66–42.41)	47.33 (20.64–63.12)	17.90 (17.41–18.39)	15.93 (15.46–16.41)	11.76 (11.36–12.18)
NFIP claims > 200% annual premium	5.04 (4.75–5.31)	12.76 (5.89–17.07)	14.04 (6.48–20.23)	16.41 (6.84–18.20)	20.66 (7.95–33.27)	5.04 (4.75–5.31)	9.32 (8.95–9.69)	3.95 (3.69–4.20)
Residual financing requirement > 1% Florida GDP	3.41 (3.18–3.64)	8.65 (3.97–12.58)	9.64 (4.74–14.68)	11.71 (4.92–13.78)	16.60 (5.87–27.97)	3.81 (3.57–4.06)	5.17 (4.90–5.46)	2.08 (1.90–2.27)
Residual financing requirement > 10% Florida GDP	0.08 (0.04–0.12)	0.14 (0.10–0.53)	0.21 (0.12–0.83)	0.20 (0.13–0.60)	0.80 (0.19–2.49)	0.12 (0.07–0.17)	0.43 (0.35–0.52)	0.01 (0.00–0.02)

Table S6: **Sensitivity to the fixed insured wind fraction.** Mean outcomes from 10,000 seasons at each fixed fraction. Changes are relative to the fixed $f_W = 0.4$ analysis, which differs from the main baseline that samples f_W from Beta(4,6). Elasticities are the log difference in mean outcomes between $f_W = 0.3$ and 0.5, divided by $\log(0.5) - \log(0.3)$. Monetary values are in billion USD.

Metric (USD B or count)	f=0.1	f=0.2	f=0.3	f=0.4	f=0.5	Change, f=0.1	Change, f=0.2	Change, f=0.3	Change, f=0.5	Elasticity
Wind insured, private	1.36	2.72	4.09	5.45	6.81	-75%	-50%	-25%	+25%	+1.00
Wind insured, Citizens	0.27	0.54	0.80	1.07	1.34	-75%	-50%	-25%	+25%	+1.00
Wind un/underinsured	14.67	13.04	11.41	9.78	8.15	+50%	+33%	+17%	-17%	-0.66
FIGA residual deficit	0.09	0.38	0.77	1.21	1.68	-92%	-68%	-36%	+39%	+1.52
Citizens residual deficit	0.05	0.17	0.33	0.52	0.72	-91%	-68%	-36%	+38%	+1.50
NFIP financing requirement	0.35	0.35	0.35	0.35	0.35	+0%	+0%	+0%	+0%	+0.00
Residual financing requirement	0.48	0.90	1.45	2.08	2.75	-77%	-57%	-30%	+32%	+1.24
Insurer defaults (count)	0.78	1.38	1.81	2.15	2.43	-64%	-36%	-16%	+13%	+0.57
Largest entity deficit	0.04	0.11	0.21	0.31	0.41	-89%	-64%	-33%	+34%	+1.36

Table S7: **Model parameters and uncertainty treatment in the risk propagation framework.** Inputs are sampled within simulations, held fixed within each analysis, or varied across climate models. Stylized market and mitigation analyses change the specified inputs while preserving other assumptions.

Parameter	Value	Source	Treatment
<i>Stochastic (sampled each iteration)</i>			
Insured wind fraction f_w	Beta(4,6), mean 0.40	Florida loss reconstruction (Text S3)	Stochastic; swept 0.1–0.5 (Table S6)
Wind share of loss	Beta(8.46, 1.54) for synthetic events	Gori et al. (2025), county P_{95}	Sampled for each event. Historical and constructed scenarios use the distributions in Text S2
Company exposure within counties	Normal draws, mean TIV and standard deviation 0.15 TIV, clipped at zero	Assumed	Independent draws between company and county rows and between realizations
<i>Fixed within each analysis</i>			
Simulation size	10,000 synthetic seasons or 1,000 historical parameter realizations	Model configuration	Fixed by analysis
FHCF seasonal cap	\$17 B	FHCF 2023–2024 reimbursement contract	Deterministic
FHCF coverage election cov_i	{45, 75, 90}%	FHCF reimbursement contract	Deterministic; assigned by insurer
FHCF retention and payout multiples	12.1464 (45%), 7.2878 (75%), 6.0732 (90%); payout 11.2368; expense factor 1.10	Contract and 2023/2024 ratemaking reports (Text S4)	Deterministic
FIGA assessment cap	2% normal + 4% emergency of surviving premium	Fla. Stat. §631.57	Deterministic
Citizens Tier 1 / Tier 2 caps	15% / 10% of respective premium bases	Citizens enabling statute	Deterministic
NFIP fund pool	\$3.441 B	Congressional Research Service, IN10784	Deterministic
Intragroup support rule	group/entity surplus ratio > 10; eligible deficits cured up to the available group pool	Stylized rule; surplus from S&P filings	Deterministic
<i>Uncertain (varied across the climate ensemble)</i>			
Climate-change deltas	5-GCM ensemble median, 10th–90th percentile range	CMIP6 / MIT TC model	Uncertain (ensemble range reported)

Table S8: **Financing requirements within common groups of seasons.** Seasons are grouped by baseline economic loss, using the loss thresholds associated with the return periods described in Text S6 and combining sparse groups until at least 50 seasons are represented. The group with zero or negligible loss, up to USD 1, is retained separately. Component means are calculated from the same seasons and sum to the mean residual financing requirement. The financing share divides the mean requirement by mean economic loss in the group; it is not the average of individual seasonal ratios. Monetary values are in billion USD.

Loss bin	Seasons	Mean loss (USD B)	FIGA	Citizens	NFIP	Financing share (%)
Zero or negligible loss (up to USD 1)	2869	0.00	0.00	0.00	0.00	0.00
> 0 – 10yr (0.0-39.5B)	6130	3.97	0.02	0.01	0.00	0.78
10yr – 25yr (39.5-147.0B)	601	78.79	2.64	0.70	0.48	4.85
25yr – 50yr (147.0-246.0B)	199	189.35	14.04	4.38	2.80	11.21
50yr – 100yr (246.0-357.0B)	100	295.49	26.18	11.60	6.27	14.91
> 100yr (> 357.0B)	101	540.07	52.44	27.35	19.63	18.41

Supporting figures

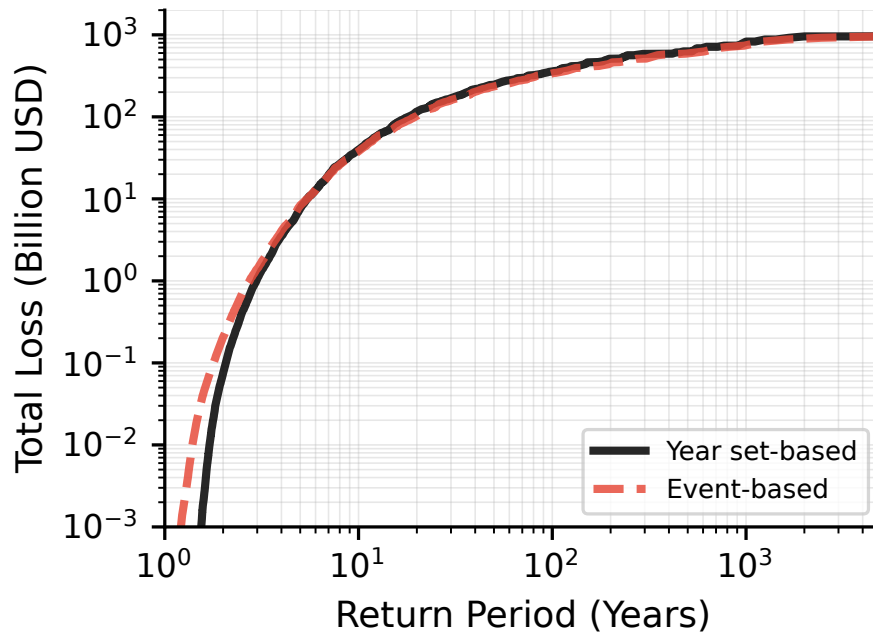


Figure S1: **Return period curves for total tropical cyclone losses in Florida.** Event-based losses (red dashed line) and seasonal aggregate losses (solid black line) are shown. Event-based return periods are derived from the empirical exceedance distribution of single events in the ERA5 synthetic tropical cyclone event set (8,800 events covering 1980–2023; Text S2). Seasonal return periods are computed from the empirical exceedance distribution of aggregate losses across simulated 10,000 tropical cyclone years (Text S5).

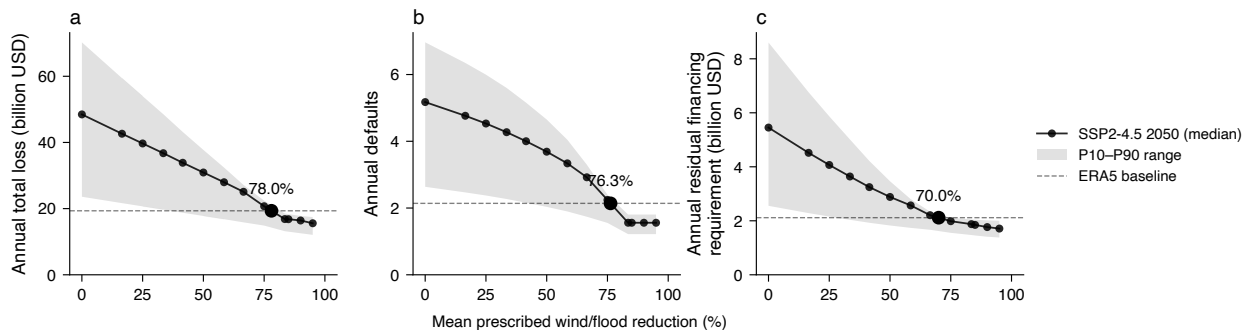


Figure S2: **Sensitivity of systemic insurance outcomes to prescribed loss reductions.** Mean economic loss, private insurer defaults, and residual financing requirement under mid-century (2041–2060) SSP2–4.5. The horizontal axis is the arithmetic mean of each tested wind and flood reduction pair, specified in Text S5. Curves add the median future-minus-historical GCM change to the ERA5 baseline. Shading represents the 10th to 90th percentile across GCM changes, and dashed lines mark ERA5. Each simulation contains 10,000 seasons. Only the nonnegative physical range is displayed; the additive climate adjustment can yield values below zero under very strong prescribed reductions.

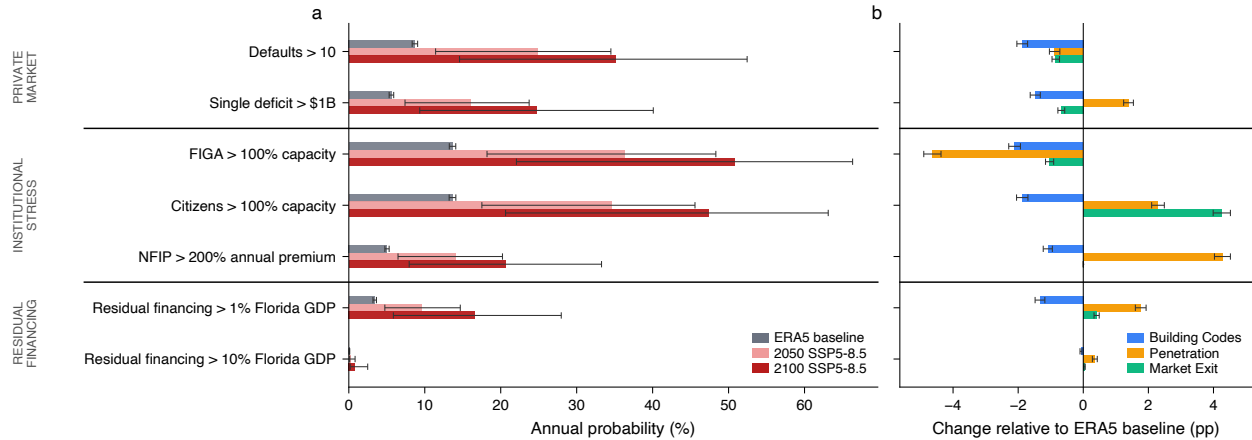


Figure S3: **Systemic insurance stress under SSP5-8.5.** (a) Annual threshold exceedance probabilities for ERA5 and mid-century and end-of-century SSP5-8.5. Future probabilities are obtained from each GCM's future-minus-historical indicator change, added to ERA5. Intervals in (a) represent the 10th to 90th percentile across the five GCM changes. These results use the same thresholds and procedure as the SSP2-4.5 comparisons in the main text. (b) The present-day policy comparison shows percentage-point (pp) changes from the ERA5 baseline, repeated from the main text, with intervals from 1,000 paired resamples of whole season rows.

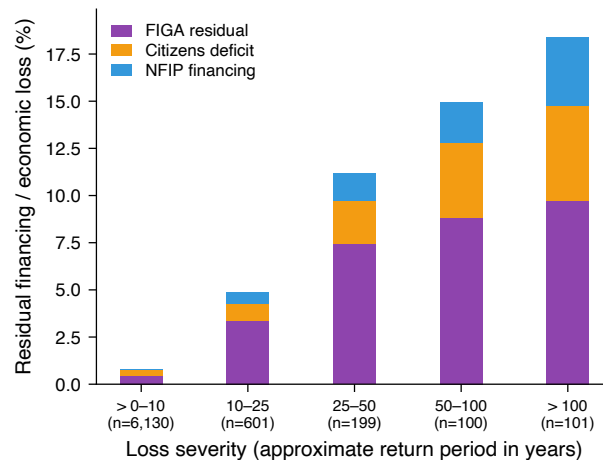


Figure S4: **Residual financing requirements across common season groups.** Each component mean is divided by mean economic loss within the same group of seasons. The stacked shares therefore sum to the ratio of mean financing requirement to mean loss. The group with zero or negligible loss, up to USD 1, is omitted. This accounting decomposition describes where losses remain and does not isolate the causal effect of individual thresholds. Table S8 provides group sizes and values.

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