FEMA Phase-Out? Catastrophic Extremes Limit Decentralization of U.S. Flood Insurance

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Abstract

The U.S. National Flood Insurance Program (NFIP) faces growing solvency and affordability pressures amid proposals to decentralize FEMA and shift disaster management to states. Many catastrophic floods span state boundaries, exposing multiple decentralized insurance pools simultaneously. Using a path-independent simulation framework that integrates risk-based premiums, hydrometeorologically-clustered flood losses, and current reinsurance contracts, we evaluate the stability of national and state-level pooling. National pooling markedly reduces systemic insolvency through cross-regional diversification, while many state pools exhibit structural fragility. State-level deficits are dominated by hyperclusters—coherent spatiotemporal losses with common atmospheric drivers—indicating that correlated loss governs failure. Since states must balance budgets and cannot borrow to cover large losses, pool liquidity constrains decentralized systems. Existing reinsurance offers limited buffering due to its misalignment with the clustered, spatiotemporal nature of hydroclimatic risk. A resilient and affordable NFIP will require hybrid financial design aligning risk-based premiums and reinsurance to balance chronic and catastrophic risk.

1) Introduction

The U.S. flood insurance system faces a structural solvency crisis. The National Flood Insurance Program (NFIP), administered by FEMA and covering nearly 90% of U.S. flood insurance policies, carries over $22 billion in debt despite a $16 billion congressional bailout in 2017, reflecting decades of chronic financial imbalance [1,2]. Established after private insurers withdrew from the flood market in the mid-twentieth century [3], the NFIP was intended to stabilize coverage for high-risk areas, but has instead become a persistent federal liability. Now, as the White House advances plans to decentralize FEMA and shift disaster management to the states [4–6], the administration claims that reducing FEMA's role would create a leaner, more accountable system better aligned with state and local priorities [7]. Unlike the federal government which can sustain debt, states are constitutionally bound to balance their budgets, exposing them to insolvency under catastrophic losses [4]. Simultaneously, private property insurers are retreating from high-risk markets such as Florida and California [8,9], shifting millions of homeowner's policies to last-resort state insurers like Florida's Citizens and California's FAIR Plan, which both already face sharp deficits and rate hikes [10]. The convergence of federal retrenchment, private withdrawals, and climate-driven extremes creates a new focal point for U.S. disaster finance: whether decentralized state insurance pools can be solvent under accelerating systemic risk.

Catastrophic flood losses that occur in highly spatiotemporally correlated clusters are the dominant source of federal debt accumulation [11]. Termed catastrophic "hyperclustering," extreme spatially and temporally clustered losses have been shown to consistently accrue debt: the eight most catastrophic clustered loss events account for over half of all recorded indemnity claims in the history of the NFIP [12]. From a physical perspective, flood losses are naturally spatiotemporally clustered, driven by organized synoptic patterns that drive clusters of storms and result in flooding [13–15]. Traditional insurance models rely on diversified, uncorrelated risk pools, but hydroclimatic clustering challenges this structure, leading to compounding losses and slow fiscal recovery [11]. Moreover, since catastrophic flood risk is not spatially uniform, tensions can emerge between regions that benefit disproportionately from federal support and those that do not [12].

Reforming the National Flood Insurance Program (NFIP) has remained an unresolved challenge for decades. Proposed solutions range from risk-based pricing [16] and multi-year insurance contracts [17] to parametric policies [18] and integration with managed retreat initiatives [19]. FEMA's recent adoption of Risk Rating 2.0 (RR2) marks a significant shift toward actuarially grounded, spatially explicit pricing, aligning with hydrologic modeling approaches for dynamic flood risk management [16,20–22]. Yet, analyses of historical "hyperclustered" flood losses show that even current risk-based premiums cannot prevent debt accumulation driven by spatially and temporally correlated extremes [12]. Concurrently, RR2 has intensified long-standing concerns about insurance affordability [23,24], with proposed premium increases exceeding 100% in several Gulf Coast states. Price increases recently spurred Senate calls for program repeal as new rates surpass the 2% median household income affordability benchmark [25]. Rising premiums can motivate households to drop coverage, widening the underinsurance gap and undermining the NFIP's foundational purpose of maintaining broad, affordable flood coverage [26].

In 2017, FEMA began purchasing traditional reinsurance to distribute NFIP risk under extreme losses [27]. In 2018, this was expanded to insurance-linked securities (ILS) in the form of FloodSmart catastrophe bonds to buffer catastrophic risks, triggered by "named storms," or tropical cyclones [27]. Beyond risk sharing, reinsurance has become an expanding market for liquidity provision during catastrophic events, ensuring claim payments even when reserves are depleted [28,29]. While the federal government can use borrowing authority to cover NFIP deficits, states must balance their budgets, leaving them far more vulnerable to shortfalls [4]. Reinsurance therefore becomes an essential liquidity mechanism under decentralized disaster management, enabling rapid payouts without unsustainable debt. FEMA's 2025 contracts provide partial coverage through traditional reinsurance for flood disasters exceeding $7 billion in indemnity, and partial ILS coverage for tropical cyclones above $6 billion [27,30–32]. However, issuance of new FloodSmart bonds for 2025 has reportedly been halted by the White House [33]. Only three events in NFIP history—Hurricanes Katrina, Harvey, and Sandy—would have met these indemnity thresholds [12], all predating FEMA's reinsurance program. Consequently, the adequacy of current reinsurance to buffer catastrophic losses, and the viability of decentralized state insurance pools under clustered regional extremes remains an open question.

We develop a simulation framework to evaluate the financial resilience of the U.S. National Flood Insurance Program (NFIP) under current Risk Rating 2.0 (RR2) premiums and 2025 reinsurance contracts, with attention to emerging proposals for decentralizing the program into state-managed pools. Because states must balance their budgets, solvency depends not only on expected losses but also on the liquidity available to pay claims when disasters occur. Our simulator tracks the evolution of reserves through sequences of clustered loss events, capturing how liquidity constraints shape solvency outcomes over time. The model combines stochastic simulation with unsupervised machine learning and game theory–inspired analysis to assess how pricing and reinsurance interact to shape solvency. Specifically, we ask:

(1) How would decentralizing the NFIP into state pools affect stability and debt accumulation relative to a unified national pool?

(2) To what extent are current RR2 premiums and reinsurance costs "fairly" distributed among states, and what regions are structural beneficiaries and cost-bearers?

(3) To what extent do spatiotemporally clustered flood events drive state-level insolvency, and which hydrometeorologic processes dominate these losses?

(4) How can pricing reforms and reinsurance strategies be co-designed to stabilize insurance systems under clustered extremes?

We structure our findings to sequentially investigate each research question: state versus national pooling (Section 2.1), state cost distribution fairness (Section 2.2), spatiotemporal insolvency triggers (Section 2.3, and pricing–reinsurance co-design (Section 2.4). We provide insights for reforming NFIP and related disaster insurance systems, with implications extending to state-regulated homeowner's markets facing similar exposure to correlated catastrophic risk.

2) Results

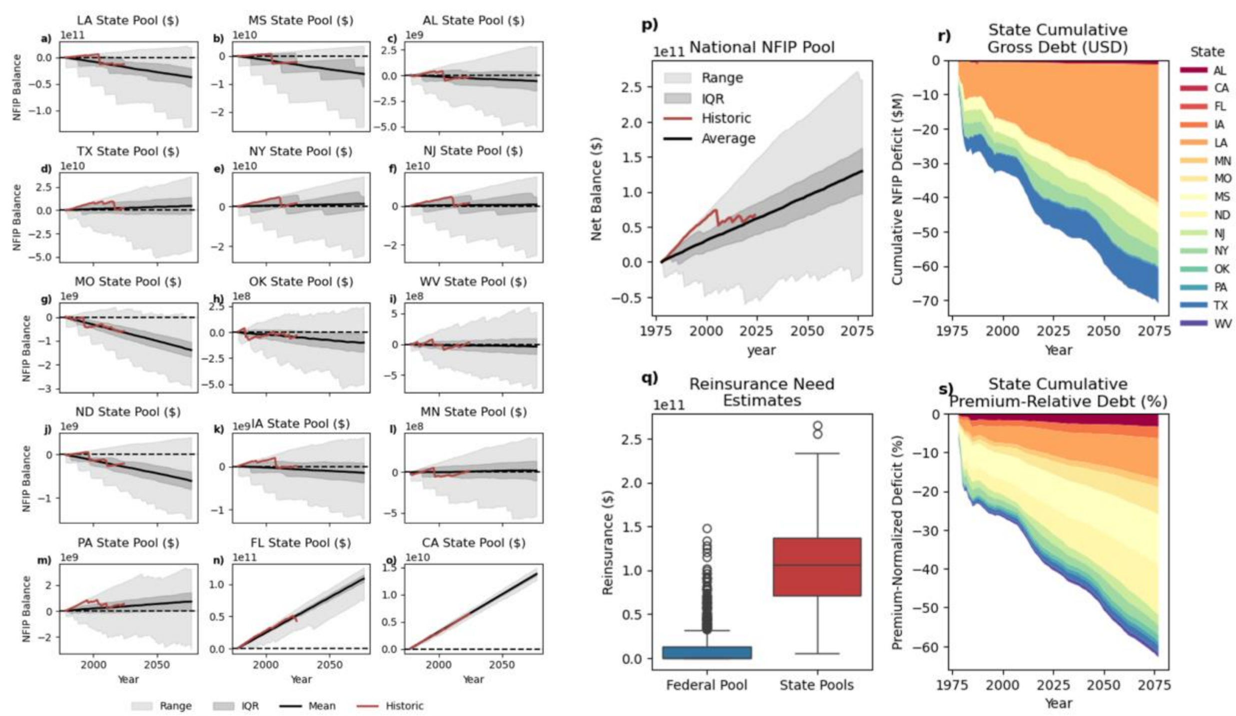
2.1) National vs. State Pooling Stability

To evaluate the financial stability of decentralized insurance, we simulate the performance of independent state pools relative to a unified national pool under historical flood loss conditions and current NFIP pricing. Because pool solvency depends on both cumulative premiums and the sequence of extreme events, we account for path dependency by resampling historical losses through 1,000 stochastic simulations of 100-year records. Each simulation uses block bootstrapping in 10-year segments to preserve interannual to decadal climatic variability [14,34]. This approach isolates structural imbalances while preserving low-frequency climate variability to reveal persistent patterns of pool failure (see SI, Sections 3 and 4 for comparison with randomly bootstrapped and historic simulations).

At the state level, pool stability diverges according to whether loss patterns are catastrophic or chronic. Southern states such as Louisiana, Mississippi, and Alabama face catastrophic, tropical-cyclone-driven losses (e.g., Hurricane Katrina) and lack sufficient premiums to recover within reasonable timeframes (Fig. 1a–c). In contrast, states with higher premiums and lower withdrawal rates (such as Texas, New York, and New Jersey) recover more quickly from major events like Hurricanes Harvey and Sandy, aided by current reinsurance coverage (Fig. 1d–f). States including Missouri, Oklahoma, and West Virginia experience persistent insolvency driven by both clustered losses and recurrent shortfalls that current premiums fail to offset (Fig. 1g–i). Riverine flood regimes in West North Central states (North Dakota, Iowa, and Minnesota) also produce large correlated losses, as seen in the 1993 Great Flood and 1997 Red River Flood (Fig. 1j–l). Finally, states with higher levels of insured assets such as Pennsylvania, Florida, and California maintain stability despite hyperclustered events (e.g., Hurricanes Ivan and Ian), reflecting the buffering effect of greater premium capacity and policy uptake (Fig. 1m–o). Overall, current RR2 pricing yields inconsistent stability across states: some remain chronically insolvent despite risk-based increases in rates.

National pooling substantially reduces systemic insolvency risk by aggregating premiums across diverse regions, buffering localized extremes, and reducing reliance on reinsurance (Fig. 1p–q). In contrast, state pools lack this diversification, causing reserves to fluctuate sharply with regional events and increasing the likelihood of debt accumulation (Fig. 1a–o). On average, the national pool exhibits near-zero cumulative debt under current pricing, underscoring the stabilizing effect of spatial risk aggregation (Fig. 1p). Examining state pool debt accumulation reveals distinct patterns of vulnerability. In absolute terms, large high-exposure states such as LA, MS, TX, NY, and NJ dominate aggregate expected debt (note FL is expected to remain solvent due to its large premium base). When losses are normalized by state-level RR2 premiums, the pattern shifts: additional fragility emerges in smaller states with limited premium capacity in AL, IA, ND, and MO (Fig. 1r–s). Vulnerability thus arises less from where losses are largest in absolute dollars than from where regionally catastrophic events overwhelm local premium reserves, exposing structural instability in underinsured, less populous regions.

Figure 1: State vs Federal Pooling



Caption: Time series of simulated independent state pools compared with a national pool for flood insurance under 1000 simulations of 10-year block-bootstrapped historic claim records from 1978 to 2024 with 2025 reinsurance contracts and risk-based premiums set by Risk Rating 2.0. Light gray represents the range of balance values for each timestep, and the dark gray denotes the 25% and 75% values across simulations. Red time series denote historic pool balances using the preserved time series of historic claims and current 2025 risk-based premiums set by Risk Rating 2.0. Expected state debt accumulation cumulatively (panel r), and with premium normalization (panel s) are provided under block-bootstrapped simulation pathways.

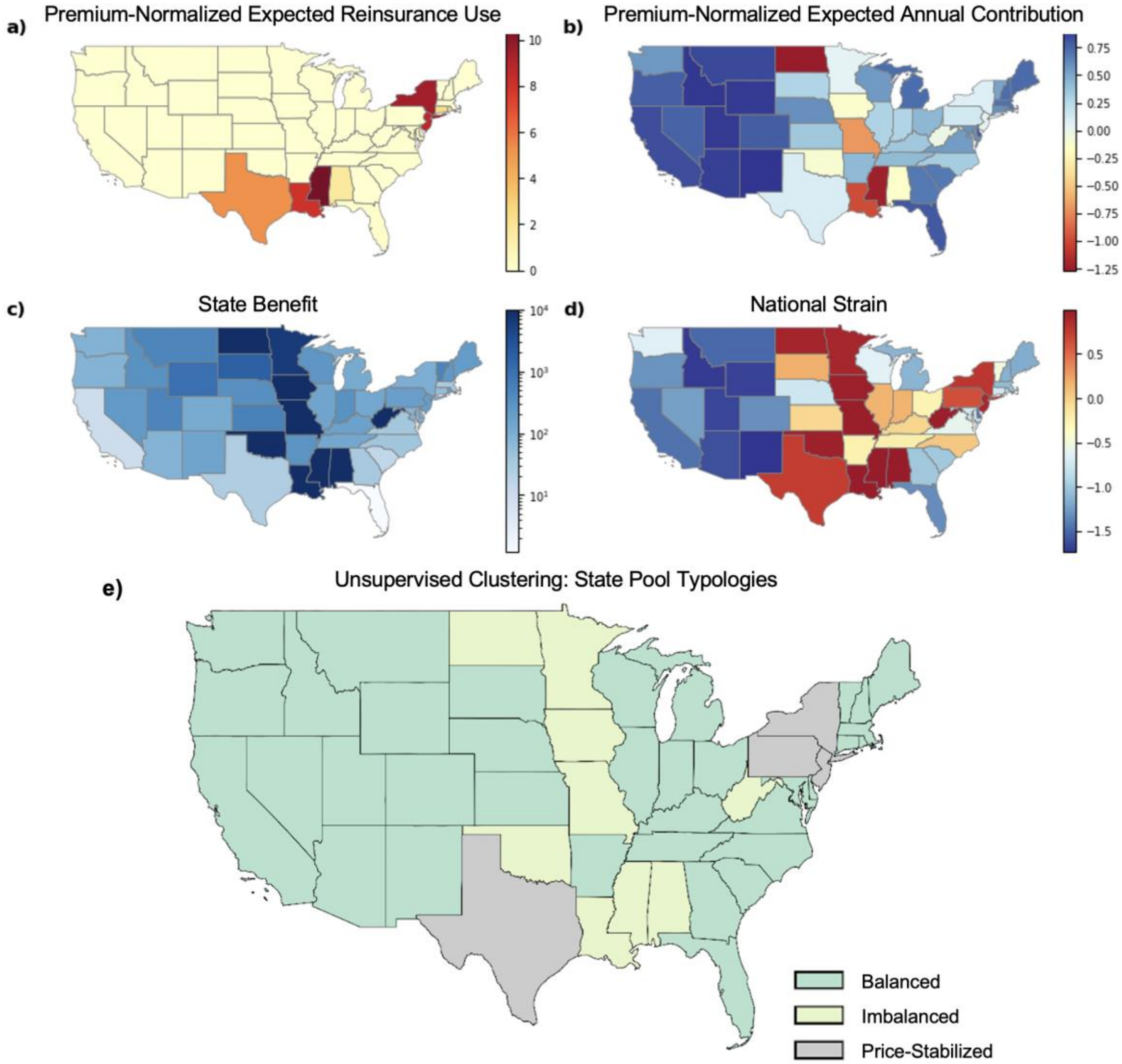
2.2) "Fair" Cost Distribution: Strain, Benefit, and Pool Typology

While national pooling enhances systemic stability, it also redistributes risk and cost unevenly among states, naturally creating net beneficiaries and cost-bearers within the insurance system. To evaluate the "fairness" of this redistribution, we formalize two complementary metrics inspired by the Shapley value in cooperative game theory: *State Benefit* ($Ben_{i,t}$), which measures the resource advantage a state gains from participating in the national pool, and *National Strain* ($Strain_{i,t}$), which quantifies the cumulative deviation of a state's share of pooled resources from that reflected by its risk-based premium over time (Figure 2, panels c and d); we also consider each state's expected pool contribution, and reinsurance use (Figure 2, panels a and b). We then use unsupervised clustering of simulated state balance trajectories to identify three distinct pooling typologies reflecting price-stabilized, imbalanced, and balanced state pools (Figure 2, panel e). Full mathematical formulations are provided in Methods (Sec. 3).

Across simulations, nine states (LA, MS, AL, MO, OK, WV, ND, IA, and MN) consistently emerge as net beneficiaries, gaining the greatest solvency advantage from national pooling (Fig. 2c). High strain and chronic instability are concentrated throughout the Mississippi River Basin (Fig. 2b,d). Because only Hurricanes Katrina, Sandy, and Harvey exceed current NFIP reinsurance triggers, this coverage concentrated in their affected states: LA, MS, AL, TX, NY, and NJ (Fig. 2a). The current national pooling system effectively transfers resources from lower-risk states in the West to high-risk, lower-income regions concentrated in the Mississippi River Basin. This redistribution yields an implicit equity benefit: five of the six states benefitting most from the national pool (LA, MS, AL, OK, WV) rank among the ten highest nationally in poverty rate, showing that national pooling acts as a *de facto* federal subsidy for regions with high hazard exposure and limited economic capacity (see SI, Section 7 for poverty levels and GDP by state). Similarly, federally financed reinsurance disproportionately benefits a small set of catastrophe-prone states with dense asset exposure, leaving others with comparable clustered risk but lower exposed assets (e.g., ND, MO) without coverage. Because FEMA currently absorbs reinsurance costs, taxpayer funds effectively subsidize these high-risk states, reinforcing de facto price subsidies in national flood-risk sharing.

To summarize state-level pooling dynamics, we use unsupervised clustering to identify three typologies of stability within our state balance time series (Fig. 2e): balanced, imbalanced, and price-stabilized states. While most states fall within the balanced cluster, TX, NY, NJ, and PA are categorized separately, largely only remaining stable under reinsured subsidy (TX, NY, NJ) or risk-pricing intervention (PA). The highest-risk cluster includes LA, MS, AL, MO, OK, WV, ND, IA, and MN which exhibit persistent mispricing or insufficient reinsurance, destabilizing their pools. Together, these findings highlight that sustainable flood insurance reform must jointly balance pricing fairness and reinsurance allocation to maintain solvency without eroding national risk-sharing efficiency.

Figure 2: Expected Costs, Strain, and Benefit for State Pool Types



Caption: Premium-normalized expected total reinsurance allotted (panel a), premium-normalized expected annual state pool contribution (panel b), final net benefit (panel c), and final system strain (panel d) under block-bootstrapped claim simulation and current 2025 RR2 premiums. Panel e depicts the Dynamic time warping hierarchical clustering (DTW-HC) results of unsupervised statewide dynamics using block-bootstrapped simulated pool balances under historical claims and 2025 RR2 premiums.

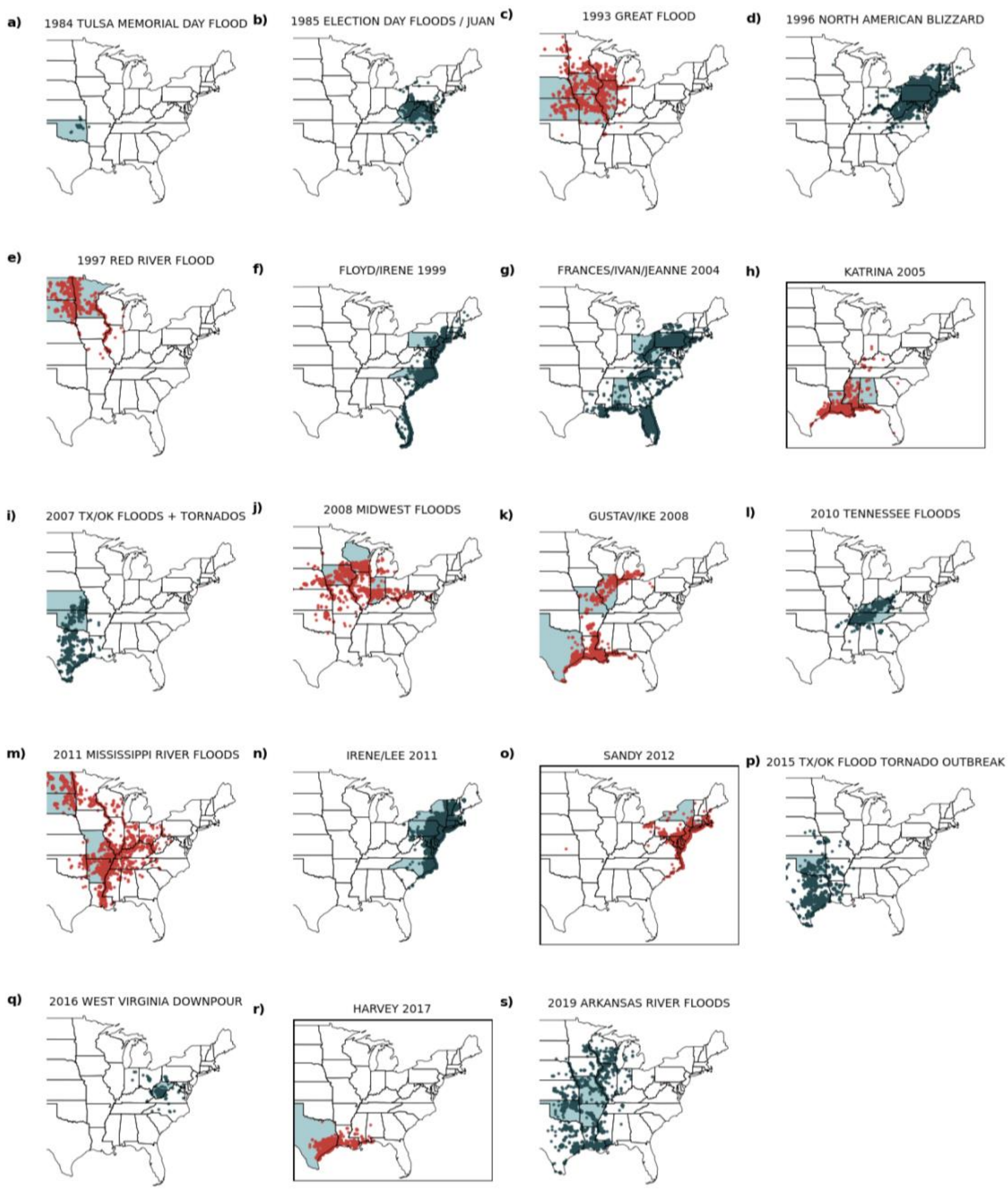
2.3) Spatiotemporal Hydrometeorologic Drivers of Pool Fragility

Building on statewide patterns of risk pooling, we isolate the hydrometeorologic extremes driving state-level insolvency. Debt accumulation consistently coincides with spatiotemporally correlated flooding, where clustered extremes overwhelm regional premium pools. To isolate physical drivers of such clusters, we examine the organization of state-relative hyperclusters which we define as coherent flood sequences induced by a common atmospheric driver, repeatedly inducing state pool debt across simulations. We focus on clusters that trigger insolvency in at least one of five simulations after a 10-year burn-in period to allow baseline accumulation. Nearly all state-level deficits arise from such organized, spatiotemporally clustered floods driven by large-scale synoptic patterns that structure damage across regions.

Across CONUS, state-level insolvency consistently arises from diverse and compound flood-generating regimes. Figure 3 shows that relative hyperclusters form through a range of hydrometeorologic drivers, including coastal and inland impact from tropical cyclones (e.g., Katrina, Harvey, Sandy, Ike, Ivan, Irene, Lee), snowmelt-driven riverine floods (1997 Red River Flood), pluvial–riverine floods (1984 Tulsa Memorial Day, 1993 Great Flood, 2008 Midwest Floods), rapid snowmelt–rainfall interactions (1996 North American Blizzard, 2011 Mississippi, 2019 Arkansas River Floods), and severe convective storm clusters (1985 Election Day, 2010 Tennessee Floods, 2016 West Virginia Downpour). Many hyperclusters involve sequential or interacting events, such as the Frances/Ivan/Jeanne (2004) and Gustav/Ike (2008) tropical cyclone sequences, where temporally proximate storms share overlapping damaging tracks. These spatiotemporally organized and synoptically linked systems often propagate far inland, producing cascading impacts across multiple basins—for instance, Gustav and Ike induced correlated failures from severe convective storms and tornadoes across Texas, Missouri, and Illinois, and the 1985 Election Day floods followed Hurricane Juan. Together, these patterns show that state-pool fragility is governed by spatially coherent, region-specific flood regimes shaped by large-scale hydroclimatic processes, such as moisture recycling and atmospheric blocking which lead to clustered failures, rather than isolated extremes.

Hyperclustered events reveal that NFIP reinsurance contracts are misaligned with this spatiotemporal structure of U.S. flood losses, triggered only by "named" tropical cyclones exceeding $6 billion in indemnity while overlooking most other catastrophic drivers. Of the 19 state-relative hyperclusters identified, only three (Katrina, Harvey, and Sandy) trigger reinsurance payouts, and just seven directly involve tropical cyclones (Figure 3), leaving roughly two-thirds of damaging clusters without coverage. Moreover, sequential tropical cyclones such as Frances/Ivan/Jeanne (2004) and Gustav/Ike (2008) are treated as separate events even if cumulative losses exceed federal thresholds within weeks. Among the twelve billion-dollar hyperclusters reported nationally [12], only five recur at the state level (Katrina, Sandy, Harvey, Gustav/Ike, and Frances/Ivan/Jeanne) demonstrating that relative, not absolute, loss magnitude determines state-pool fragility.

Figure 3: State-Relative Hyperclusters



Caption: Spatial organization of state-relative hyperclusters during severe loss across the NFIP historical record under block-bootstrapped claim simulation. Red clusters induce consistent failure (one out of five simulations) even after pricing intervention under both full RR2 premiums (with applied CRS discounting) and current 2025 RR2 premiums, while dark green clusters induce consistent failure (one out of five simulations) under only current 2025 premiums. State pools that exhibit instances of failure (debt accumulation) under such clusters with full RR2 premiums are shaded light blue. Hurricanes Katrina, Sandy, and Harvey are boxed to denote they trigger current 2025 reinsurance contracts.

2.4) Balancing Reinsurance and Pricing Interventions

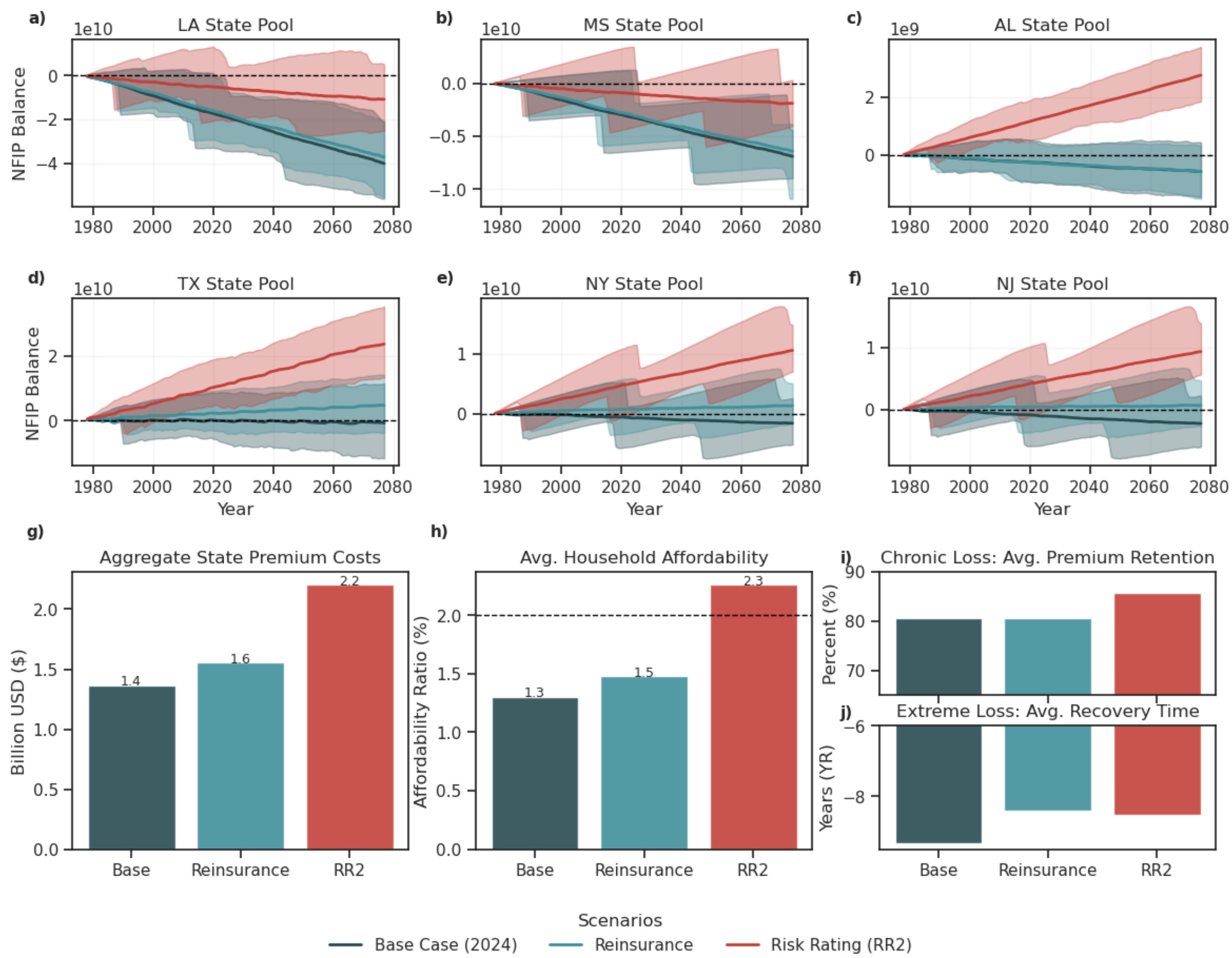
Using our simulation model, we evaluate how risk-based pricing and reinsurance stabilize state pools across three policy configurations: (a) a base case of current 2025 premiums without reinsurance, (b) fully phased-in RR2 pricing (accounting for Community Rating System discounts), and (c) current 2025 premiums combined with FloodSmart and traditional federal reinsurance contracts (Fig. 4a–f). We focus on six states affected by historical reinsurance-triggering events (Katrina, Sandy, and Harvey)—New York, New Jersey, Texas, Louisiana, Mississippi, and Alabama.

Both full RR2 pricing and existing reinsurance stabilize losses from Hurricanes Harvey and Sandy, maintaining solvency in Texas, New York, and New Jersey. However, all strategies fail under Katrina in Mississippi and Louisiana, since current reinsurance covers only 12% of losses between $7–9 billion and 26% between $9–11 billion—offering limited protection against an event of roughly $26 billion. Results highlight the structural limits of FEMA's tiered reinsurance coverage and the need for contracts that scale with correlated catastrophic risk. Even with fully phased-in risk-based pricing, Louisiana and Mississippi remain insolvent, underscoring the limits of premium increases in highly correlated pools.

Comparing aggregate cost and affordability (Fig. 4g–h), we find that full RR2 premiums exceed the 2% affordability threshold relative to median household income. While FEMA currently funds reinsurance premiums (effectively distributing costs across all taxpayers), redistributing these costs proportionally to states that trigger payouts would yield lower average homeowner costs than full RR2 implementation, even when distributed between this limited set of states. Because public insurance pools are not designed for profit, sustained positive growth despite major losses (observed under full RR2 rates in Alabama, Texas, New York, and New Jersey) may indicate overpricing rather than resilience. Reinsurance can achieve comparable solvency stabilization at lower aggregate cost, preserving affordability and reducing the likelihood of policyholders dropping coverage due to price. Overall, full RR2 likely overprices risk by embedding catastrophic losses into premiums that could instead be buffered through multi-state reinsurance.

Sustainable flood insurance depends on balancing chronic and catastrophic risk [12]. We evaluate indicators of two primary sources of state pool fragility: (1) underpriced premiums that limit pool accumulation, and (2) "overwithdrawal" from catastrophic, space–time-clustered events that deplete liquid reserves (Fig. 4i–j). Using the withdrawal indicator $w_{i,t}$ that indicates whether a given state i withdraws funds from their pool or does not at time t (Figure 4), we compare the average non-negative annual contribution to each state pool as a share of total premiums (panel i) with the number of years of full premiums needed to recover a typical loss year (panel j). The first metric targets chronic, recurrent underpricing; the second captures catastrophic overwithdrawal requiring reinsurance. Results show that reinsurance effectively buffers clustered, high-impact losses but does not address persistent underpricing (panel i), while both reinsurance and full RR2 pricing achieve similar loss dampening overall (panel j). Given RR2's higher homeowner costs, reinsurance emerges as a more efficient strategy for managing catastrophic, correlated losses, while risk-based premiums should target chronic, recurrent shortfalls.

Figure 4: Risk-Pricing vs Reinsurance Intervention



Caption: Comparisons between reinsurance and risk-rating RR2 pricing intervention across state pooling outcomes (a-f), aggregate costs (g), average household premium affordability (h), premium retention (i) and average loss recovery time (j) for LA, MS, AL, TX, NY, and NJ under block-boostrapped simulation. State-level costs, affordability, premium retention, and recovery time can be found in the SI, Section 6, Figure S3. Note current 2025 premiums reflect a partially phased-in RR2 risk-rating, as current law [35] limits rate increases by 18% annually, and RR2 was implemented in 2023.

3) Discussion

Recent federal proposals to scale back FEMA programs including the National Flood Insurance Program (NFIP), and the growing reliance on state-based last-resort insurers (such as Citizens and the California FAIR Plan) underscore the urgent need to evaluate the financial feasibility and risk exposure of decentralized state insurance systems. Using a path-independent simulation framework, we assess current NFIP pricing and reinsurance structures under both unified national and disaggregated state pooling configurations informed by hydrometeorologically clustered flood insurance claims data. Our findings reveal systemic trade-offs between solvency, affordability, and fairness across pooling regimes and identify four key principles to guide NFIP reform and broader natural-disaster insurance design:

(1) Maintain national pooling for catastrophic stability and risk diversification. State-level pools heighten exposure to regional risk concentrations, whereas a unified national pool provides spatial buffering and greater resilience to hyperclustered, catastrophic losses.

(2) Incorporate fairness metrics in cost distribution between states. The relative benefit states gain from national pooling and the strain they place on shared reserves should inform fair reinsurance pricing and redistribution of federal support.

(3) Expand reinsurance coverage beyond tropical cyclones and "named" storms. Catastrophic and correlated losses frequently stem from riverine flooding, severe convective storms, snowmelt-driven floods, and compounding storm sequences, which are largely neglected with current reinsurance triggers.

(4) Balance chronic and catastrophic risk with risk pricing and reinsurance. A financially stable and affordable NFIP will depend on aligning risk-based premium structures to cover recurrent losses, reinsurance to absorb catastrophic extremes, and adaptive cost-sharing to sustain long-term solvency.

Our work underscores the dual role of reinsurance as both a loss-transfer and liquidity mechanism for managing compounding, spatiotemporally clustered flood risk. Covering such hyperclustered losses remains a core challenge for disaster insurance, especially as decentralization shifts fiscal responsibility to states that cannot borrow to bridge shortfalls. Current national coverage is inadequate for a non-unified NFIP: FEMA's 2025 reinsurance contract transfers only $757.8 million in risk—an amount trivial relative to the federal government's liquidity capacity and to the scale of potential flood losses—despite being spread across 27 reinsurers [32]. This raises a broader policy tension: while private reinsurance adds relatively modest value to a centralized federal program, it becomes essential for state-based systems that lack federal borrowing authority. The limited coverage of existing contracts has motivated FEMA's use of insurance-linked securities (ILS) such as FloodSmart catastrophe bonds, which provide pre-arranged capital for rapid claim payouts. Yet these instruments remain narrowly focused on tropical cyclones, neglecting other catastrophic hydrometeorologic drivers. Future reinsurance and ILS structures should expand liquidity access across perils and regions, balancing cost efficiency with the need for immediate payout capacity under clustered extremes. Because reinsurance and ILS premiums total hundreds of millions of dollars annually and are unnecessary in low-risk regions, FEMA should consider targeted cost displacement and parametric design approaches to maintain affordability.

Climate variability and evolving market dynamics must be incorporated into future flood-risk engineering. A key limitation of our study is its reliance on historical loss data; our simulations do not capture projected changes in hydroclimatic extremes under a nonstationary climate. We also evaluate existing federal pricing and reinsurance contracts rather than optimizing their design, reflecting current institutional and regulatory constraints. Future work should therefore assess state-level solvency and pooling performance under climate evolution, alongside shifts in reinsurer demand, risk appetite, and price sensitivity. As catastrophe risk intensifies, a fundamental policy question remains unresolved: should reinsurance and insurance-linked securities (ILS) in the United States function as private market instruments or as federally backed public mechanisms for liquidity provision? Senate proposals for a Federal Reinsurance Program have met pushback from private reinsurers, reflecting this tension [36]. Developing forward-looking reinsurance and ILS frameworks that jointly account for climate-driven loss clustering, capital-market behavior, and public liquidity needs will be essential for long-term flood-insurance sustainability.

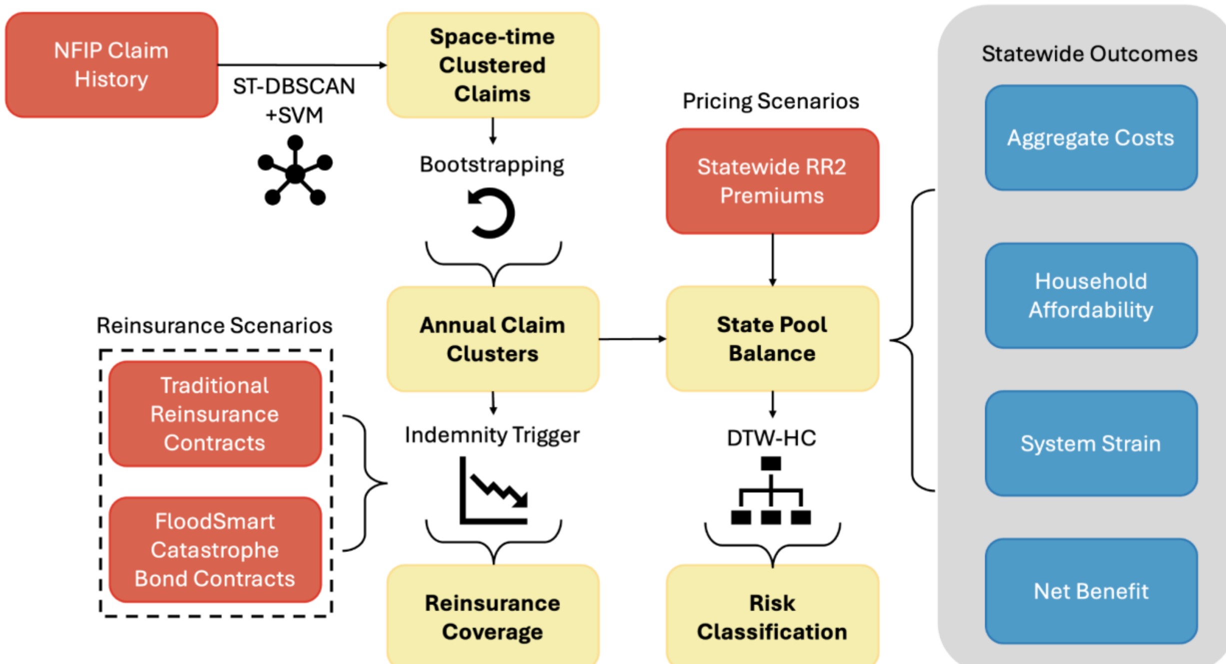
The reforms proposed here extend beyond the NFIP to broader U.S. homeowner and hazard insurance markets, now strained by climate-driven extremes. As major insurers withdraw from high-risk states such as Florida and California [9,37] and last-resort state insurers face severe deficits [10], there is an opportunity to redesign national insurance systems around multi-peril, spatially diversified pools that integrate floods, wildfires, and droughts (crop insurance) to strengthen solvency and share risk more equitably. Such diversification could rebalance the regional pattern of benefit and strain revealed in our analysis, distributing financial responsibility more fairly across states. Achieving this balance will require a hybrid financial structure and adaptive financial tools [38] designed in coordination across climate science, engineering, finance, and policy. A climate-ready framework should integrate financial preparedness with physical resilience, linking reinsurance and insurance-linked securities to infrastructure and land-use planning so that insurance not only redistributes losses but helps reduce them.

4) Methods

4.1) Flood Insurance Pool Simulator

To assess the solvency and liquidity of statewide and national insurance pools across the historical record, we use current and fully-realized risk-based premiums (RR2) and FEMA's 2025 reinsurance contracts under an ensemble of plausible loss sequences. To evaluate these dynamics, we develop a simulator for NFIP risk pooling as depicted in Figure 5.

Figure 5: Model Schematic



Caption: Model schematic for flood insurance state pool simulation.

Our model implements FEMA's 2025 reinsurance policies (see SI, Section 1, Table S1 for full details on 2025 reinsurance policies) paired with bootstrapping of spatiotemporally clustered, inflation-adjusted NFIP indemnity losses from 1978 to present to remove path dependence in pool accumulation. At each simulated year, indemnity claims are grouped by space–time clusters, with coverage from multi-layer reinsurance and insurance-linked securities (ILS) allocated proportionally to affected states according to loss share. Premiums are held constant at current risk-based levels, or fully-realized, and are credited annually to each state's balance, while uncovered claims are debited. We explicitly track each state's cumulative NFIP balance over the simulation period, recording the timing and magnitude of transitions from positive to negative balances—corresponding to years when liquidity is exhausted and external financing would be required. For each such transition, the simulator identifies the highest-loss cluster driving the deficit. If it is above the reinsurance trigger threshold, it triggers reinsurance payout. If the cluster is a "named storm" or a tropical cyclone above the indemnity threshold it triggers ILS payout.

We run 1,000 simulations of 100 years each, resampling annual loss records with replacement. We do this with random sampling for each year, and in 10-year segments, or "runs" to better preserve the sequencing associated with sub-decadal to decadal climatologic variability following previous studies [34] for nonstationary risk quantification. State-level summaries are stored for every simulation year, including adjusted claims, reinsurance and ILS recoveries, total covered losses, premium, net NFIP payout, contribution, and cumulative balance. Final-year balances and key events are compiled across simulations for comparative solvency analysis of the national pool versus decentralized state pools. Data for historic claims and current premiums is sourced from OpenFEMA, and all reinsurance terms are derived from publicly reported FEMA contracts [30,32]. Fully-realized RR2 premiums are provided by FEMA directly.

In our analysis, we consider debt as relative to the pooled balance of a given state. For instance, anytime claims outweigh available pooled funds and the balance becomes negative, we consider this as state debt in our modeled simulation. We consider debt accumulation as an indicator of insurance pooling failure, as it results in a lack of funds available for liquid withdrawal in the case of further loss. Additionally, for claims filed, we assume the state to be responsible for payment, and thus must accrue funds from elsewhere (whether by loan by the federal government or otherwise) to supply such funds to policyholders. In our simulation, we neglect effects of interest rates that are likely to accrue further debt on behalf of the state in order to isolate the given loss-driver. The motivation of neglecting interest accrued on statewide debt is to better isolate the magnitude of loss exceedance that places excessive burden on the system in the case that pricing could be adjusted to cover said loss, rather than assess debt from interest in the case of chronic insolvency.

To evaluate reform scenarios, we analyze existing federal pricing and reinsurance structures rather than hypothetical optimized designs to reflect current policy limits. NFIP reinsurance contracts, which are established through negotiated agreements among FEMA, private reinsurers, and brokers, represent institutional and market constraints rather than freely optimizable features of system design. The Homeowner Flood Insurance Affordability Act of 2014 caps annual premium increases at 18% [35]. As a result, current Risk Rating 2.0 (RR2) premiums, introduced in 2023, remain only partially phased in across regions. Given these constraints, we assess three intervention scenarios:

1. Current premiums without reinsurance — representing baseline exposure under partial RR2 implementation.
2. Fully implemented RR2 premiums (accounting for Community Rating System adjustments) — representing a counterfactual equilibrium of risk-based pricing.
3. Current premiums with existing federal reinsurance contracts (including FloodSmart ILS) — representing current hybrid practice.

Results for a fourth scenario capturing both fully-realized RR2 premiums and reinsurance contracts can be found in the SI, Section 5, Figure B4. Because current federal reinsurance only triggers payouts for Hurricanes Katrina, Sandy, and Harvey, our state-level evaluation of these scenarios focuses on the states affected by those events: New York, New Jersey, Texas, Louisiana, Mississippi, and Alabama.

4.2) Quantifying Pooling "Fairness": Benefit & Strain

We consider the competitive internal dynamics present within a federally-pooled flood insurance system that emerge between states as discussed previously [12]. In order to address the destabilizing dynamics that emerge between states within the current NFIP, we must consider an individual state's contribution to the wider pool in relation to the *"benefit"* they receive to be included rather than self-insuring. Inspired by the Shapley value in cooperative game theory [39] that defines the value of an individual player or coalition to the larger whole, *benefit* defines the value of the whole to the individual player. Consider state i across S total states, at time t' for T total timesteps. We define an aggregate risk-based premium $p_{i,t'}$, claim withdrawn from the pool $c_{i,t'}$, and statewide default NFIP balance $b_{i,t'}$ such that:

$$b_{i,t'} = \sum_{t=0}^{t'} (p_{i,t} - c_{i,t})$$

Note that at $t = 0$, $b_{i,0} = p_{i,0}$. In the context of an insurance pool, we consider the net benefit $Ben_{i,t}$ of the pool to state i to be equal to the sum of the available pool at time t' across all states over the maximum of the value of the individual state's contribution to the pool, or some nominal ϵ (thus ensuring positive values, here we use $\epsilon = 0.1$):

$$Ben_{i,t'} = \frac{\sum_i^S max(b_{i,t'}, \epsilon)}{max(b_{i,t'}, \epsilon)}$$

Note that at $t = 0$, $Ben_{i,0} = \frac{\sum_i^S p_i}{p_i}$. We illustrate a simple single-round calculation of benefit at $t = 0$ in the SI, Section 2, Figure S2, panels a-c.

In parallel, we define the $Strain_{i,t'}$ state i places on the pool at time t' by its normalized deviation from the original benefit the state obtains from the NFIP under Risk Rating 2.0. We then scale state contributions to the aggregate catastrophe bond premium by the proportion of the sum of $Strain_{i,t'}$ placed on the pool in aggregate and the state's premium itself, p_t. More specifically:

$$Strain_{i,t'} = \frac{Ben_{i,t'} - Ben_{i,0}}{Ben_{i,t'}}$$

Thus, while *benefit* captures the value of the unified national pool to the individual state, *strain* denotes the disproportional risk each state places on the larger national pool in relation to its pricepoint.

4.3) Clustering Typologies of Balance Pools

To summarize different state pooling typologies over time, we applied an agglomerative hierarchical clustering framework to group states according to similarities in their historical NFIP claim balance trajectories. Prior to clustering, each state's time series was standardized to zero mean and unit variance to remove differences in absolute magnitude and emphasize temporal patterns.

First, pairwise dissimilarities between states were computed using Dynamic Time Warping (DTW) as introduced in [40] using the package *dtw* from *tslearn* in Python. Given two sequences:

$$X = (x_1, x_2, \dots, x_n) \qquad Y = (y_1, y_2, \dots, y_m)$$

We define the local cost matrix and the cumulative cost matrix D recursively as:

$$d_{i,j} = (x_i - y_j)^2$$

$$D_{i,j} = d_{i,j} + min(D_{i-1,j}, D_{i,j-1}, D_{i-1,j-1}), \text{ where } D_{1,1} = d_{1,1}$$

The DTW distance between X and Y is then given by:

$$DTW(X,Y) = \sqrt{D_{n,m}}$$

This formulation permits non-linear alignments in time, allowing the comparison of sequences with phase shifts and differing rates of change.

The resulting symmetric distance matrix $\Delta = [\delta_{pq}]$, where $\delta_{pq} = DTW(X^{(p)}, X^{(q)})$, is then supplied to an agglomerative hierarchical clustering algorithm as in [41] using the hierarchy package from scipy in Python. Starting from N singleton clusters, the distance between two clusters A and B under average linkage is defined as:

$$d(A,B) = \frac{1}{|A||B|} \sum_{i \epsilon A} \sum_{j \epsilon B} \delta_{i,j}$$

At each iteration, the two clusters with the smallest $d(A,B)$ are merged, and the process continues until a single cluster remains.

The resulting dendrogram is cut at $k = 3$ clusters, chosen to balance interpretability and within-cluster homogeneity. We repeat this process across all simulations and choose the mode clustering assignment. Cluster assignments were integrated with TIGERLINE geographic data for mapping.

4.4) Hydrometeorologic Spatiotemporal Clustering of Losses

To capture the spatiotemporal structure of flood losses, we use unsupervised learning to identify hydrometeorologic loss clusters from NFIP insurance claims. Specifically, we apply ST-DBSCAN [42], a spatiotemporal extension of DBSCAN [43] previously used for clustering extreme weather events [44–46] based on the reported dates and locations of losses.

ST-DBSCAN groups nearby events through an iterative, density-based process defined by three parameters: a spatial threshold τ_S, a temporal threshold τ_T, and a minimum number of points per core event $MinPts$. Starting from a random point $i_{x,y,t}$, the algorithm identifies neighboring points within the specified spatial τ_S and temporal τ_T radii. If at least $MinPts$ neighbors fall within this three-dimensional radius, the process continues iteratively; otherwise, clustering stops. If a claim is unclustered, it is denoted by the null cluster (–1).

Although DBSCAN is often criticized for challenging parameter selection [47], we validate our clustering using FEMA disaster declarations, as done in previous studies using NFIP claims data [12,46]. We first apply DBSCAN under τ_T at the county level, followed by ST-DBSCAN for spatiotemporal clustering as seen in [46]. To ensure continuity across long temporal clusters, we use proxy points distributed in time at a distance ϵ (where $\epsilon \ll 1$) less than τ_T across each temporal cluster, then apply ST-DBSCAN. A sensitivity analysis assessed cluster characteristics across varying threshold parameterizations and is further detailed in the SI of [46].

We highlight that we adopt a hydroclimatic to hydrometeorologic approach for spatiotemporal flood-damage clustering, emphasizing large-scale, multi-state phenomena and hyperclustered events (e.g., presidentially declared disasters) rather than localized or catchment-based floods. For tropical cyclone sequences with similar tracks in a short period of time (such as Frances, Ivan, and Jeanne in 2004), these hydrometeorologically sequential storms are often clustered together, capturing compounding effects. However, for simulation, damage from each tropical cyclone must be separated, as they are reinsured separately. To split such clusters containing sequences of tropical cyclones, we pair hurricane track data (HURDAT2) from NOAA with our hydroclimatic clusters. We first identify candidate storms for each claim using a spatiotemporal gate around the claim (distance to the track and time difference along the trajectory) and assign provisional labels based on the nearest track position in space–time. We then refine these assignments using an unsupervised support vector machine (SVM) classifier [48] in joint space–time coordinates (latitude, longitude, and loss date). The process yields temporally coherent, storm-specific tropical cyclone subclusters in which each claim is associated with a physically plausible tropical cyclone, while candidate tracks with no consistent spatiotemporal linkage retain zero damage.

4.5) Cost, Affordability, and Pool Stability Metrics

To assess the success of reinsurance and risk-pricing intervention scenarios described in Section 4.1, we develop a series of metrics to capture outcomes to aggregate costs, household affordability, and pool stability. Aggregate costs are summed across all household premiums and reinsurance costs, pooled across all six states. To calculate affordability, we use county-level US Census data for median household income (MHI) paired with total policy counts $P_{c,t}$ and full risk-based premiums from RR2 $R_{c,t}$ for county c at year t. Insurance affordability $a_{c,t}$ for county c at year t is calculated as:

$$a_{c,t} = \frac{R_{c,t}}{P_{c,t} * MH_{c,t}} * 100\%$$

We consider affordability outcomes in relation to the 2% threshold of MHI, as commonly adopted in economic-hydrologic studies for water affordability [49–51].

We aim to consider two main types of stability risk in our insurance pool design: 1) the handling of hyperclustered, catastrophic risks that are spatially and temporally correlated, 2) the pricing of chronic and recurrent risks within the statewide pool as identified in [12]. These factors together help us to determine which states are at risk of debt accumulation. To do so, we consider two indicators of overwithdrawal risk.

The first, $c_{i,t}$ is an indicator variable that represents times in which a state's claim volume exceeds their current balance, indicating that the state will go into debt from the given loss year. If $c_{i,t}$ is true, we have pool instability and debt is accumulated in the state pool simulation, otherwise, the pool balance remains positive. Specifically, this occurs when we exceed our balance with the given claim volume:

$$c_{i,t} = Bool(c_{i,t} > b_{i,t})$$

The second, $w_{i,t}$ is an indicator variable that represents times in which a state contributes less to their personal statewide pool than they withdraw. Specifically, this occurs when annual claims exceed state total premiums under the given claim volume:

$$w_{i,t} = Bool(c_{i,t} > p_{i,t})$$

Note that we expect $w_{i,t}$ to be true in a number of years as many years a state will withdraw more than they contribute, but we would be concerned about underpricing if it is true with *persistence*. We then use the $w_{i,t}$ indicator to construct two diagnostic metrics across scenarios (Results, Fig. 4i–j):

(i) the average annual *positive* contribution to the pool as a fraction of premiums when $w_{i,t}$ is false, capturing chronic pricing sufficiency; and
(ii) the number of years of full premiums required to recover a typical loss event when $w_{i,t}$ is true, capturing catastrophic overwithdrawal severity.

Together, these metrics allow us to separate how risk-based pricing reforms and reinsurance differently stabilize recurrent versus clustered catastrophic losses within risk pools.

Data Availability

All NFIP redacted claims, policies, disaster declaration, and Community Rating System data is publicly accessible and can be accessed through FEMA's OpenFEMA portal. HURDAT2 hurricane track data is accessible through NOAA's NHC Data Archive. Median household income data is available through the US Census American Community Survey.

Code Availability

We provide open access code for our simulation model and all analytic processes conducted in this manuscript in the following GitHub repository.

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