Catastrophic "Hyperclustering" and Recurrent Losses: Diagnosing U.S. Flood Insurance Insolvency Triggers

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Abstract

Although a cornerstone of U.S. flood risk preparedness since 1968, the National Flood Insurance Program (NFIP), is burdened by insolvency. Despite pricing and risk assessment reforms, systemic failures persist, resulting in accumulation of billions in federal debt. This study presents an interdisciplinary framework integrating qualitative synthesis, unsupervised machine learning, and game theory to diagnose triggers of insolvency. We identify catastrophic "hyperclustering" as large-scale flood events spanning days to weeks and induced by a common hydrometeorological driver, which dominate claim volumes often in regions of high asset density. We find chronic annual losses arise from recurrent claims, emphasizing the need for proactive managed retreat from high-risk areas. Our findings support targeted NFIP reform and broader risk management, particularly as climate extremes intensify the homeowners' insurance crisis. We argue that long-term resilience requires aligning financial, structural, and non-structural interventions with distinct regional risk patterns—whether driven by hyperclustering, recurrent losses, or both.

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1) Introduction

Despite a $16B debt forgiveness by Congress in 2017, the U.S. National Flood Insurance Program (NFIP) remains over $20B in debt today, threatening its long-term sustainability (Elliott, 2015; FEMA, 2024a). Created in 1968, the NFIP was originally formed due to the withdrawal of private insurers from flood insurance markets nationally, motivated by heavy-tailed, "uninsurable" risk from flooding (American Institutes for Research, 2005). Due to its history of insolvency, scrutiny of the NFIP is rampant with concerns ranging from mispriced premiums (de Ruig et al., 2022), limited willingness to pay for flood insurance (Netusil et al., 2021), and lack of affordability within the program (Kousky & Kunreuther, 2014). With increases in billion-dollar disasters rampant across the country (NCEI, 2024), disaster risk is becoming an increasingly pressing national concern. A major source of tension during the 2024 U.S. Congressional Budget negotiations and near government shutdown was the continuation of funding for the NFIP (Forbes, 2024). The program has been temporarily reauthorized 32 times since 2017 (Hapgood, 2025), and renewal again remains pending reauthorization (FEMA, 2024b). With Congressional discussions of reforming the program (US Committee on Banking, Housing, and Urban Affairs, 2025), and Executive calls to eliminate FEMA programs altogether (Weissert et al., 2025), evaluation of programmatic failures is imperative.

Previous discussions for reform within the NFIP have largely centered around pricing adjustments and purchasing regulation to better reflect risk, although exact sources of failure in the program itself remain uncertain (de Ruig et al., 2022, 2023). Program subsidies that include the Community Rating System (CRS) for affordability, and grandfathered policies with lower, out-of-date rates have been subject to scrutiny (Gourevitch & Pinter, 2023; Kousky et al., 2016, 2021). Parametric insurance and regional index insurance strategies have been suggested as solutions (Khalil et al., 2007; Tellman et al., 2022). In 2023, FEMA implemented a new pricing mechanism for policies to better reflect flood risk called Risk Rating 2.0 (FEMA, 2023). However, little research has examined the efficacy of the new risk-based premiums to recover past and future risks. Lack of insurance uptake is also cited as a major issue (Netusil et al., 2021). As the primary mechanism that drives flood insurance adoption nationally (Kousky, 2018; Kousky et al., 2020), FEMA flood maps have also been exhaustively questioned (Board on Earth Sciences and Resources/Mapping Science Committee et al., 2009; Flores et al., 2023; Maidment, 2009; Xian et al., 2015). However, economists have long claimed that disaster insurance markets are not designed to handle catastrophic, fat-tailed risk distributions (Kousky & Cooke, 2012). A longstanding question is whether pricing adjustments can buffer risk enough to recover from such catastrophic losses.

Addressing catastrophic flood losses necessitates a physical understanding of drivers of hydroclimatic extremes. Hydroclimatic risk is highly spatially and temporally compounded, organized by lasting synoptic events (Bonnafous & Lall, 2021). Although failure manifests predominantly through financial losses within the market-based insurance system, large losses may be considered realizations of spatiotemporally clustered extreme hydrometeorological dynamics (Nayak et al., 2025). The nonstationary, clustered dynamics of hydrologic extremes have long been studied (Bonnafous & Lall, 2021; Jain & Lall, 2001), but the recent focus on "compound extremes", including spatiotemporally clustered damages (Zscheischler et al., 2020), necessitates focus on these clusters and their subsequent realizations within financial systems such as insurance, managed retreat, disaster aid, and supply chains (Haraguchi & Lall, 2015; Kousky, 2018; Mach et al., 2019; Nayak et al., 2025).

Traditional flood frequency analysis strategies are point-based and as such do not address spatiotemporally clustered risk, which dominates realized flood damages: flood insurance failure is a symptom of a larger plague for disaster risk management. Hydrologists and civil engineers typically consider decadal to multidecadal timescales for risk mitigation design (Task Committee of Urban Water Resources Research Council, 2018). While financial analysts and economists can be limited in modeling long time horizons due to focus on the fiscal year, recent studies have also called into question the credibility of the typical engineering 100-year flood design strategy due to repeated losses and infrastructure failure occurring under conditions with much lower severities (Hwang & Lall, 2024; Nayak et al., 2025). Further, there has only been a limited analysis of the space-time exposure to extreme floods (Amonkar et al., 2023), and the role of large-scale flooding and recurrent localized flooding in determining losses and draws from NFIP has not been investigated. Thus, future risk management strategies require an intermediary and interdisciplinary perspective that accounts for structure in both human-made markets and hydroclimatic-driven risks.

We introduce an interdisciplinary framework to diagnose insolvency triggers, or failure points, within the NFIP. We develop a holistic, systems-level approach that pairs subject expert qualitative interviews with data-driven machine learning to identify clear sources of failure for reform. Our analysis introduces the concept of catastrophic "hyperclustering": a new paradigm for disaster risk management that captures extreme spatiotemporal correlation in disaster damage driven by large-scale, severe compound flooding. We discuss the dangers of repeated losses, and the need for proactive managed retreat and home buyout programs that subsidize relocation from locations with critical risk. Our work provides critical implications for the future of the NFIP, and insights beyond flood insurance to larger disaster management (Eaglesham, 2023).

2) Results

To identify drivers of NFIP insolvency failure and debt we first use inflation-adjusted, annualized claims to identify regions of expected net loss under current risk based-premiums (Methods, Section 4.1), paired with qualitative synthesis (Methods, Section 4.2) and simple normal-form games to illustrate motivations for internal conflict in the current system. Next, we employ unsupervised spatiotemporal clustering (Methods, Section 4.3) on loss data to identify and evaluate hotspots (Methods, Section 4.4) of space-time clustered losses and chronic, repeated losses. We identify “hyperclusters” as extreme instances of clustered space-time damage, defined using two metrics - i) a space-time contiguous loss exceeding $1 billion, and ii) a threshold approach for the sum of inflation-adjusted claim damage cost exceeding 99.9% of clusters in total damage claims in line with assessment of previous disaster damage assessments and threshold-based risk communication (Bell & Tobin, 2007; NCEI, 2024; Pielke Roger A. et al., 2008). Additionally, we consider the frequency of presidential disaster declarations as an indicator of hypercluster risk. We define risk of unclustered, recurrent claims by i) the count of properties by county that have made multiple claim filings historically through the NFIP, ii) the count of claims by county that are not associated with space-time contiguous losses in unsupervised cluster analysis. Finally, we summarize findings with an aggregate risk index for flood insurance insolvency nationally using indicators of 1) net expected loss, 2) hyperclustering, and 3) recurrent loss. To do so, we employ combinatorial game theory across objective entropy-based weightings and expert-informed subjective weightings (Methods, Section 4.5). A summary of our risk assessment framework is depicted in Figure 1.

Figure 1: Insolvency Risk Assessment Framework

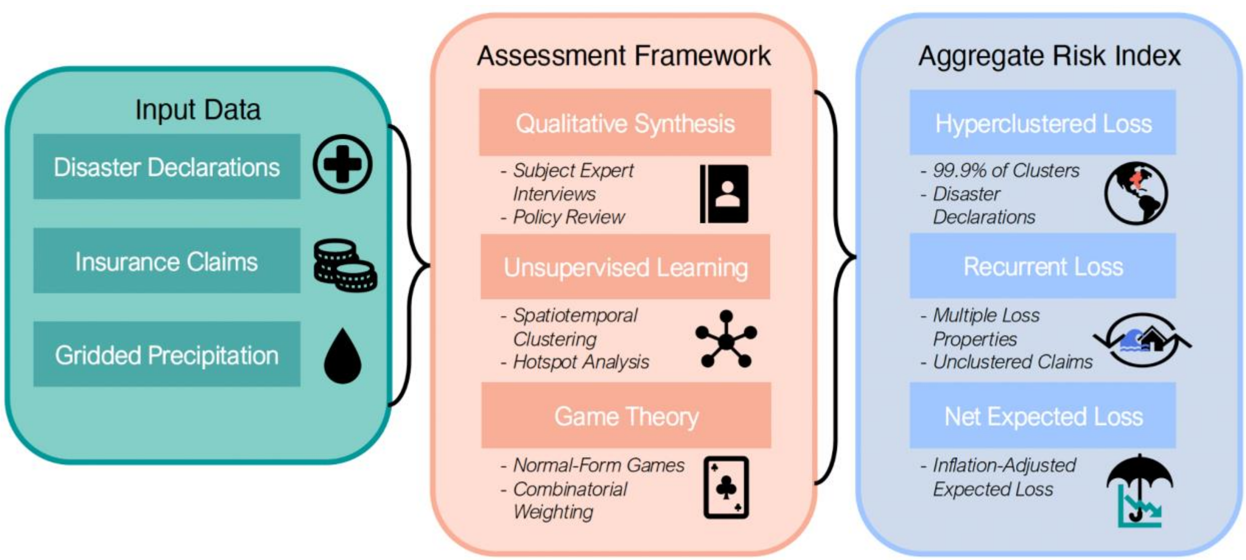


Figure 1: Methodological framework from data inputs to aggregate insurance insolvency risk.

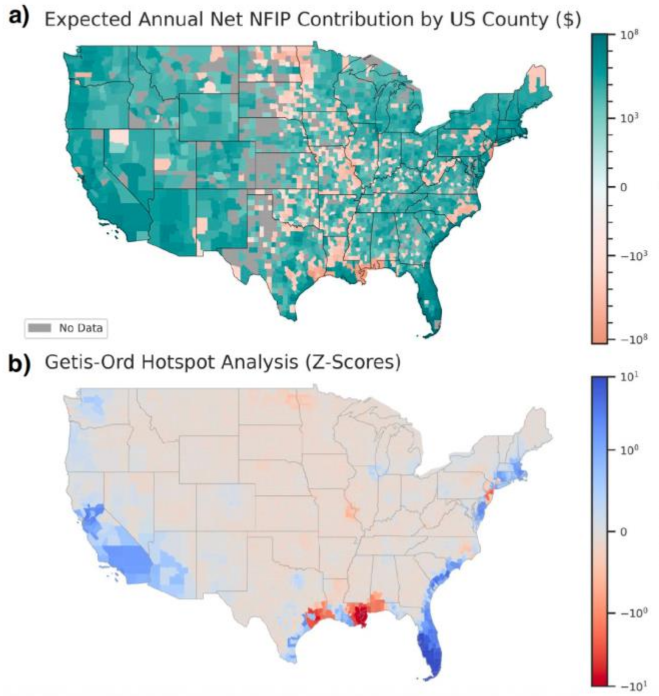
2.1) Expected Net Losses Under Risk-Based Premiums

A clear symptom of insurance pricing failure is when a region’s expected losses cannot be recovered by premium cost over time, leading to local insolvency. Although typically insurers have a portfolio to buffer regional risk, premiums are ideally priced to recover such expected losses. Motivated by repeated historical programmatic insolvency in the NFIP, Risk Rating 2.0 (RR2) was implemented by FEMA in 2023 to update NFIP premium rates to be more reflective of property flood risk (FEMA, 2023). Here, we use 2024 risk-based premiums under RR2 (in lieu of historic, underpriced premiums), to consider expected regional losses under flood risk rating metrics (see Methods, Section 4.1 for data descriptions). With the current risk-based premiums and historic annualized, inflation-adjusted claims aggregated by county, we evaluate the extent to which prior claims can be recovered by new risk-based premiums.

Under the new heightened premium scheme, historic expected failures outweigh premiums on aggregate for many counties (Figure 2). In aggregate, RR2 is able to recover historic losses, representing a sum that amounts to over four times that of historic premiums. However, by region, the ability of RR2 premium rates to recover historical claims varies. Counties with expected net loss are largely within the Mississippi River Basin (panel a). Hotspot analysis (see Methods, Section 4.4) shows significant expected losses in major coastal cities in the South along the coasts of Texas, Louisiana, Mississippi, and Alabama, as well in the Northeast in New Jersey and New York (panel b). Surprisingly, aggregate risk-based premiums largely recover claim costs in Florida and other counties along the East Coast that may have been expected to be insolvent. This is likely driven by high insurance uptake and increased risk-based premiums, particularly in Florida. A similar dynamic emerges in California, where uptake and premium cost outweigh expected claims. Socio-economic demographics of counties with an expected insurance loss are reported in the SI, Section 2.

Considering internal system dynamics, we can also conceptualize counties with expected gains as subsidizing those with expected losses. We illustrate these unstable regional competitive dynamics caused by disproportionate expected losses within the NFIP with a series of two-player normal-form games (Figure 2, panels c, d, e). Consider insurance as a pool of collective buy-in, in which a given community pays a nominal annual fee (premium) reflecting their risk so that in the case of a low-probability hazard, the community is able to withdraw funds (claims) from the common pool. We consider a game between two players which are represented by two different counties, each with an expected annual contribution to the insurance pool, E_1 and E_2 respectively. Each county can choose to “self-insure” in which they keep their own regional insurance pool for their community, or to “join” in which they merge insurance pools with their opponent. Pools are only joined if both players can agree. It is in the best interest of each regional player (in our case a given county) to diversify their portfolio of risk to expand the available pool of resources (panel c). Thus, in the case in which each county has an expected gain we reach Nash stability under cooperation, where both players join. However, it is not in the best interest of a regional player to do so if their opponent is expected to withdraw more funds than reflected in their annual premium payments (panels d and e). Using game theory, we illustrate that under the current NFIP risk-based prices, competitive unstable dynamics emerge between counties due to regional expected losses within the general pool (panel d).

Figure 2: Risk-Rating 2.0 Expected Net Losses, County-Level Hot Spots



c)

		County 2 (Gain): *Self Insure*	County 2 (Gain): *Join*
County 1 (Gain)	*Self Insure*	E_1, E_2	E_1, E_2
County 1 (Gain)	*Join*	E_1, E_2	**E_1+E_2, E_1+E_2**

d)

		County 2 (Gain): *Self Insure*	County 2 (Gain): *Join*
County 1 (Loss)	*Self Insure*	$-E_1, E_2$	$-E_1, E_2$
County 1 (Loss)	*Join*	**$-E_1, E_2$**	$-E_1+E_2, -E_1+E_2$

e)

		County 2 (Loss): *Self Insure*	County 2 (Loss): *Join*
County 1 (Loss)	*Self Insure*	**$-E_1, -E_2$**	$-E_1, -E_2$
County 1 (Loss)	*Join*	$-E_1, -E_2$	$-E_1-E_2, -E_1-E_2$

Figure 2: NFIP expected net contributions (panel a) and hotspot analysis (panel b) under Risk Rating 2.0 premiums and claims history spanning 1978 to 2024. Colors are displayed on a logarithmic scale as shown in color bars. Expected claims are aggregated by region and annualized, divided by number of years on record per region. Premiums are aggregated by region and taken directly from 2024 reported Risk Rating 2.0 premium rates. Hotspots are extracted using the Getis-Ord statistic (see Methods, Section 4.4), and Z-Scores for all counties are displayed in panel b. All prior claims are CPI-adjusted based upon the federal urban CPI Index provided by the US Bureau of Labor Statistics. Illustory normal-form games of competitive dynamics between counties operating under expected loss and gain are shown in panels c, d, and e. Nash equilibria are bolded.

2.2) Spatiotemporal Hyperclustering

Although expected losses reflect loss recovery regionally, the analysis begs the question whether hotspots for failures are driven by recurrent patterns of mispriced risk, or singular catastrophic events that induce massive unrecoverable losses (Kousky & Cooke, 2012). In order to identify spatially and temporally correlated losses and extreme catastrophic events, we use unsupervised machine learning to identify spatiotemporally clustered (see Methods, Section 4.3 for clustering details) insurance claims (Figure 3, panel a). "Hyperclustered" dynamics emerge from our clustering analysis: although over 90% of claims belong to spatiotemporal clusters, the top eight clusters by total cost outweigh the sum of all other historic claims (panel c). Hyperclusters are largely found in the South and Northeast, driven largely by hurricanes: ten out of the twelve billion-dollar clustered events being hurricane-induced (panel b). In examining the empirical distribution of clusters by the total sum of claims, we find the billion-dollar event threshold to be in the 99.83% of clusters in terms of total damage claim cost, and report a 99.9% threshold of $2.38 billion for the claim sum by cluster. Between 1978 and 2024, twelve clustered events exceeded the billion-dollar threshold (panel b). Of the billion-dollar events, eight events exceed the 99.9% threshold and four of these events (Hurricane Katrina, Hurricane Sandy, Hurricane Harvey, and Hurricane Ian) exhibit loss totals that exceed the total of 2024 risk-based premiums in aggregate across the entire country (panel d). This shows the extent to which these hyperclustered events are largely uninsurable under standard price recovery models, the top four events independently overwhelming a risk-priced insurance system (panel d).

Figure 3: Hyperclusters and Spatiotemporal Clustering

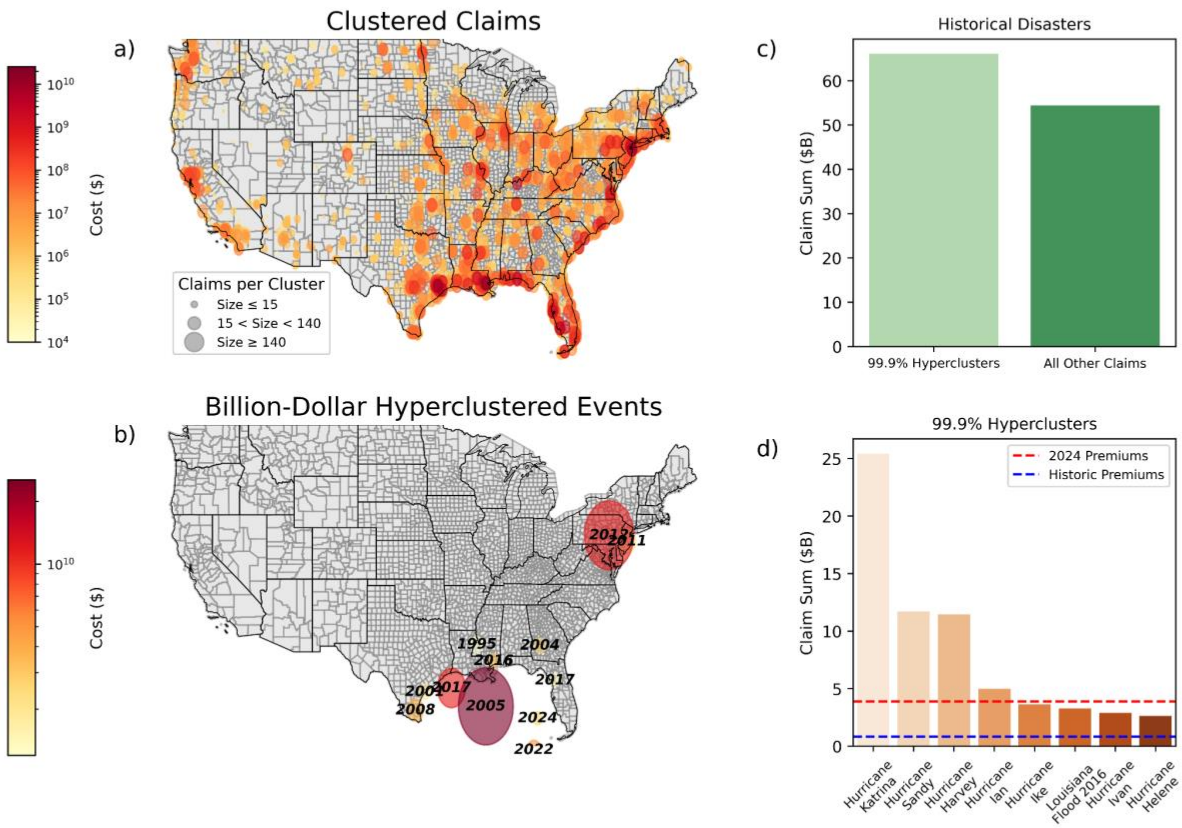


Figure 3: Spatial distribution of clustered and "hyperclustered" flood-inducing events. Spatiotemporal clusters are extracted using ST-DBSCAN (see Methods, Section 4.3) under thresholding parameters: a space threshold of three degrees latitude/longitude, time threshold of five days, and a minimum cluster size of seven. A cluster size of 15 falls at the 50th percentile of cluster size, and 140 claims at the 90th percentile, denoting size cutoffs for panel a. Parameters for clustering are optimized under validation, and sensitivity is detailed in the SI, Section 4. All claims are inflation adjusted to 2024 using urban CPI values provided by the US Bureau of Labor Statistics.

We also examine temporal dynamics of insolvency. Specifically, we use 2024 risk-based premiums and examine temporal variation in the countywide net expected annual balance, using the historical record of inflation-adjusted filed claims. We evaluate when chronic insolvency occurs under historic annual clustering with and without hyperclustering. In Figure 4, we show that the top five hyperclusters cause billions of dollars in expected debt for the program (panel a). However, if we remove hyperclusters (under both the 99.9% and the billion-dollar definitions) (panel b), the balance of the program is able to recover claims losses. Results indicate that while the system cannot recover the history of annual claims with current risk-based premiums, hyperclusters are largely driving failure. Without the eight 99.9% hyperclusters, the program is able to recover claims across the history of annual claims with risk-based premiums, and without the billion-dollar hyperclusters, the program recovers claims while maintaining over $1B in premiums each year. This is essential for covering salaries, operations, and the continuous management of the program. We note that eleven out of twelve billion-dollar hyperclustered events and all eight 99.9% events occurred in the 21st century, potentially indicating influence of climate change (Yin et al., 2018), population growth in floodplains (Tellman et al., 2021), and/or deterioration of infrastructure (Petroski, 2016) on damaging floods in recent years. We find that in the absence of hyperclustering of insured assets, insolvency and NFIP debt becomes much less probable under current risk-based premiums.

Figure 4: Time Series of Insolvency Sensitivity to Hyperclusters under Risk-Based Premiums

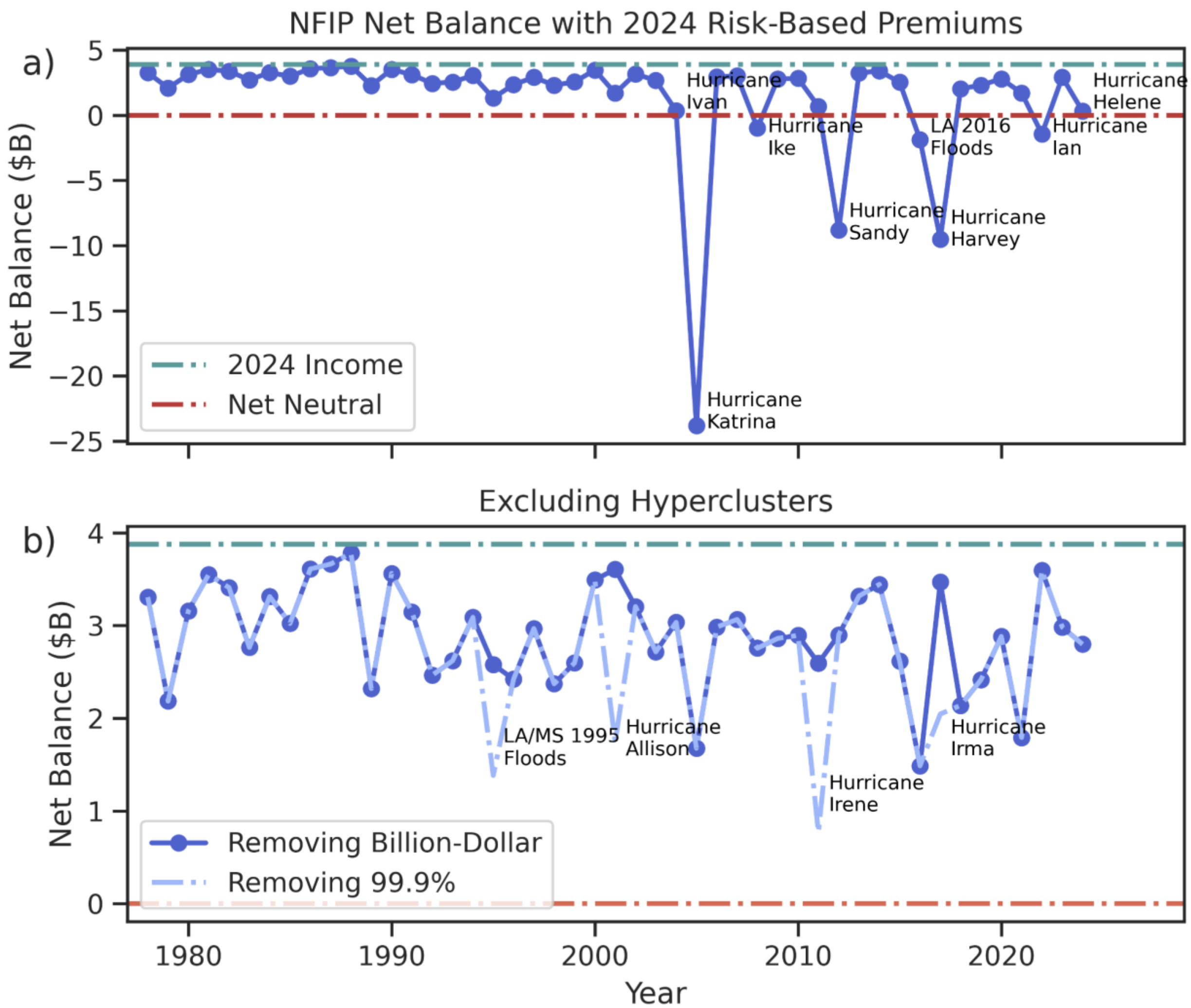


Figure 4: Time series of temporal points of insolvency under 2024 risk-based premiums and historical annual losses, inflation-adjusted (using CPI-U) from 1978 to 2024. Panel a highlights the historic time series while panel b removes 99.9% hyperclusters (labeled as failure points in panel a) and billion-dollar hyperclusters (labeled in panel b).

As indicators of regional failure, we perform a hotspot analysis (see Methods, Section 4.4) to identify regions prone to hyperclustering. In Figure 5, we examine counties directly implicated by hyperclustered events (panel b) as well as counties implicated by flood-related Presidential Disaster declarations (see SI, Section 3 for categorization) scaled by aid disbursements (panel a). Historically significant hotspots for hyperclustering are largely found on the coasts of Texas, Louisiana, Alabama, Mississippi, New Jersey and New York, with some risk highlighted along the coast of North Carolina and Southern Florida. Disaster declaration hotspots (panel a) indicate a higher risk in Florida and the Great Lakes region than those displayed in historic hyperclustered events (panel b). We find that the mean billion-dollar hypercluster exhibits a claim sum of nearly $6B in comparison to a mean cluster loss of $17M (panel c). We also find significantly higher mean precipitation return periods associated with hyperclusters than all claims (panel d), indicating a higher event intensity for these events.

Figure 5: Hyperclustered, Catastrophic Disaster Hotspots

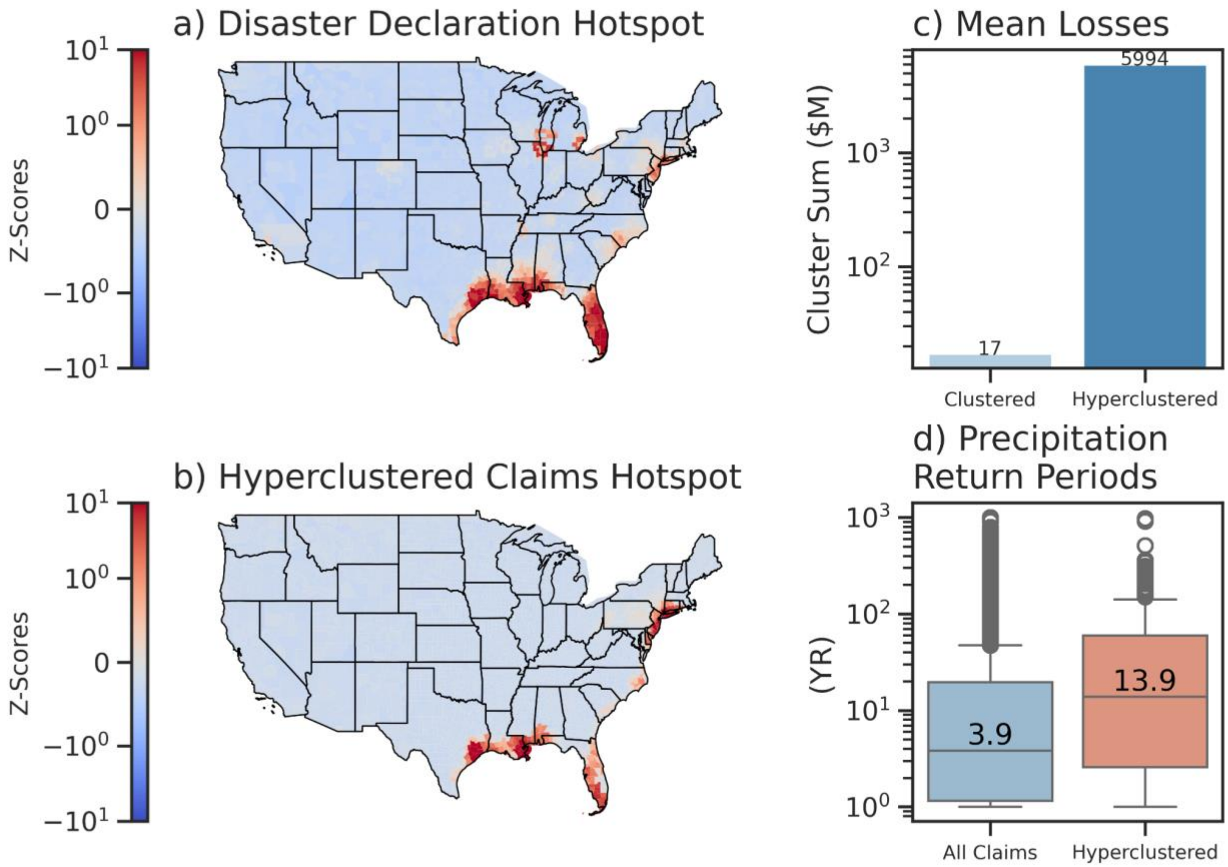


Figure 5: Getis-ord hotspot analysis (see Methods, Section 4.4) for flood-related disaster declarations and hyperclustered events by county across the contiguous United States (panels a and b). Mean losses by hypercluster and cluster by inflation-adjusted cluster sum (under CPI-U) are compared (panel c) as well as the difference in mean precipitation return period between all claims and hyperclustered events. Precipitation return periods reflect the preceding daily maximum event within 30 days of loss using MSWEP county-level aggregated values from (Nayak et al., 2025) and detailed further in Methods, Section 4.1.

2.3) Recurrent, Unclustered Losses

Another major pain point for insurance failure identified by stakeholders (see SI, Section 1) was high-risk properties experiencing repeated, low-intensity failures due to being located in risky areas. Unclustered, recurrent risk is characterized by losses that are not found to be associated with nearby space-time damage clusters, yet exhibit repeated loss on an annual basis (Figure 6). We analyze unclustered claims (panel a) as well as a database of multiple-loss properties from FEMA (panel b). Similar regions of risk emerge across both datasets in southern and east coastal regions, as well as major cities such as Chicago, Los Angeles, San Francisco, Chicago, and St. Louis, which likely all have higher populations of risky waterfront properties (panel b). Unclustered claims lead to an average of \$63M in losses annually (panel c). As anticipated, unclustered claims have nearly annual return periods for precipitation, corroborating that very frequent events drive losses (panel d) in these settings. Across all years, unclustered losses amount to over \$2B in damages. Although these losses are not solely driving the system insolvency, they are a pain point for continuous losses that is adding additional stress to the system for properties that are likely largely placed in highly risky regions, begging the question of whether these areas should be receiving continuous payouts or being relocated.

Figure 6: Unclustered, Recurrent Loss Hotspots

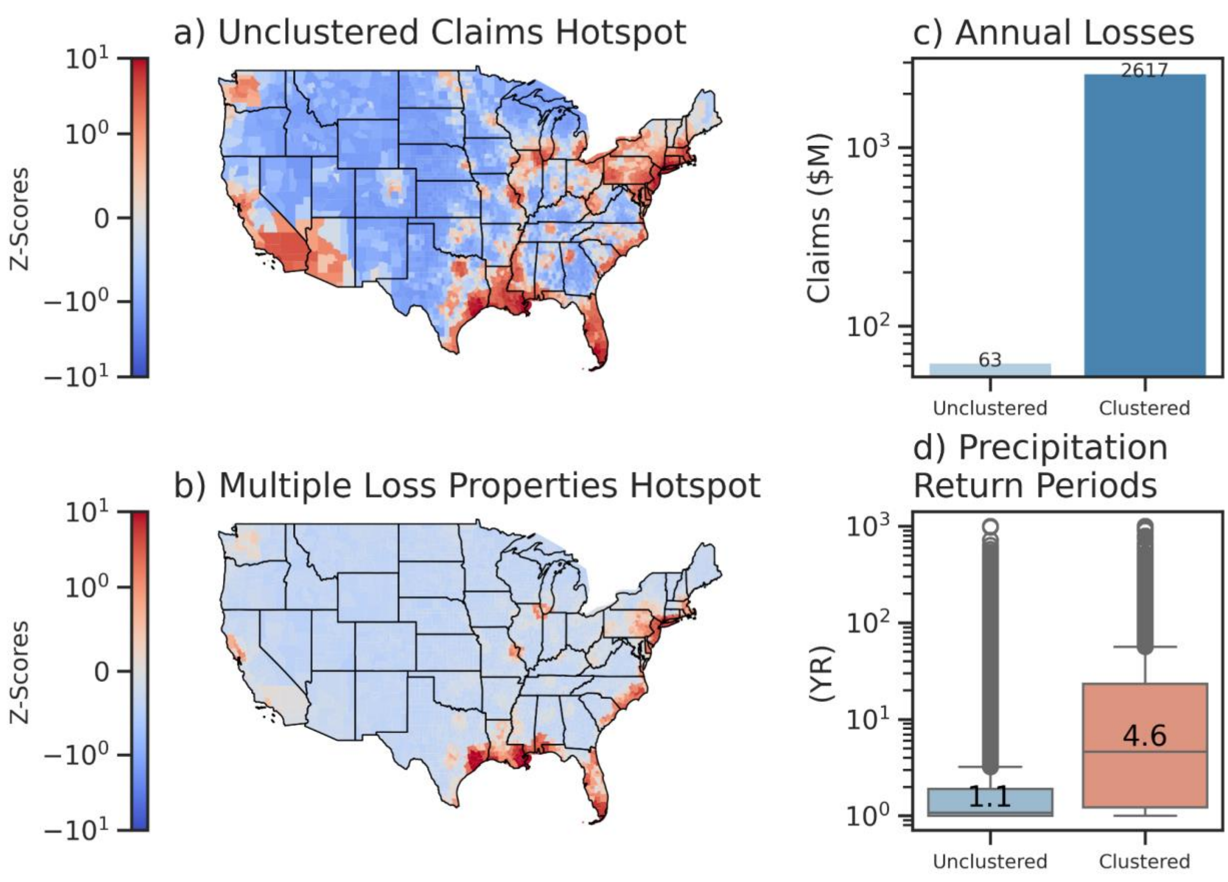


Figure 6: Getis-ord hotspot analysis (see Methods, Section 4.4) for unclustered insurance claims and multiple-loss properties by county across the contiguous United States (panels a and b). Annual mean losses for claims that are clustered and unclustered (under CPI-U) are compared (panel c) as well as the difference in mean precipitation return period between clustered and unclustered losses. Precipitation return periods reflect the

preceding daily maximum event within 30 days of loss using MSWEP county-level aggregated values from (Nayak et al., 2025) and detailed further in Methods, Section 4.1.

2.4) Summary and Aggregate Insolvency Risk Index

We summarize our findings by creating a novel aggregate risk index for insurance insolvency based upon metrics identified across qualitative and quantitative analysis (Figure 7). We integrate findings from expert-informed qualitative synthesis with analytically-derived objective weighting criteria using the subjective-objective combinatorial game theoretic weighting approach first introduced by (Lai et al., 2015). Subjective weights are discovered through qualitatively-informed ranking (see Methods, Section 4.2) followed by the Analytic Hierarchical Process (AHP), and objective weights are derived from each spatial dataset with Entropy-based Weighting (EW) as detailed in Methods, Section 4.5. The two sets of weights are then aggregated with combinatorial game theory (detailed further in Methods, Section 4.5). Our aggregate index includes metrics of 1) county-level expected net losses (Figure 2), 2) hyperclustering risk (Figure 5, panel b), 3) flood-related Presidential disaster risk (Figure 5, panel a), 4) concentration of multiple-loss properties (Figure 6, panel b), and 5) concentration of unclustered claims (Figure 6, panel a). We provide subjective weighting criteria, objective weighting, and combinatorial weighting based upon game theory in the SI, Section 5. We find the highest levels of aggregate risk in dense metropolitan areas at risk of hurricane impact, specifically Houston, Texas, New Orleans, Louisiana, and New York City (panel a) where asset value density is high. Heightened levels of risk are identified along the coast of Louisiana, Mississippi, Alabama, South Florida, North Carolina, New Jersey and New York, as well as along the Mississippi River (panel b). Aggregate risk analysis suggests these regions are in need of additional funding mechanisms that are regionally-driven in order to mitigate their inordinate levels of flood risk. We underscore that for policy analysis, each indicator metric and the combined index are valuable, since from a policy action perspective it is important to understand the type and magnitude of the risk, as well as the collective risk across types.

Figure 7: Aggregate Flood Insurance Insolvency Risk Index

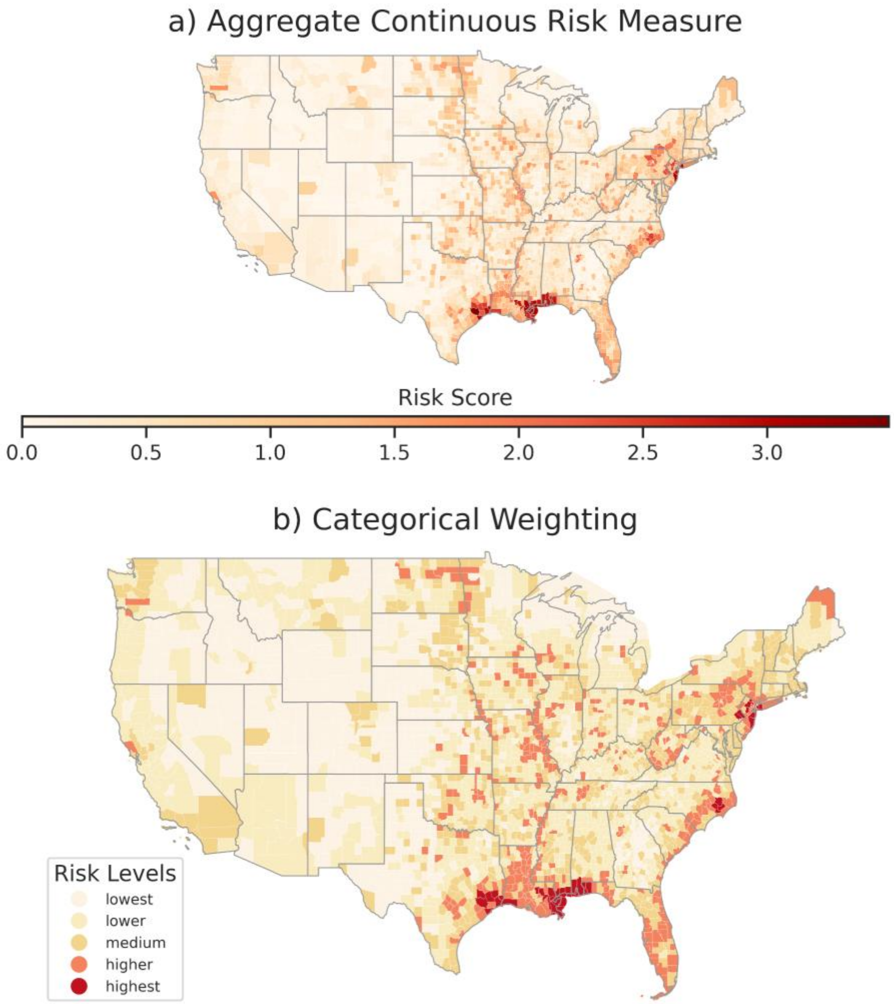


Figure 7: Aggregated flood insurance insolvency risk index developed using combinatorial game theory between subjective weighting with the analytic hierarchical process (AHP), and objective weighting with the entropy weighting (EW) method. Index aggregates 1) expected net loss by county under Risk Rating 2.0, 2) historic hyperclustering concentration, 3) historic flood-related presidential disaster aid concentration, 4) multiple loss property concentration, and 5) unclustered claim concentration. Results are presented in continuous risk scores (panel a) following (Lai et al., 2015) and discrete binned categories (panel b) using k-means clustering.

In summary, we find that NFIP insolvency failure and debt is largely driven by catastrophic hyperclustering that is not accounted for in the design of the current risk-based premium schemes. In addition, we identify critical regions prone to recurrent failure that are in need of urgent systemic intervention. A summary of major findings is provided:

1. Under inflation-adjusted, annualized losses and current risk based-premiums, there are significant coastal hotspots of expected net loss in the NFIP across the South in Texas, Louisiana, Mississippi, and Alabama, and the Northeast along New York and New Jersey.

2. Hyperclusters account for the majority of flood insurance claims: the top eight events by damage cost accounting for over 50% of all historic insurance payouts. Without insured hyperclustering, insolvency and NFIP debt becomes much less probable under current risk-based premiums.
3. Recurrent losses occur with precipitation events with regionally low intensity and an expected annual frequency, losing the NFIP on average \$63M annually and a sum of \$2.38B in total.
4. In aggregate, we find regions most at risk are large, densely populated metropolitan areas with hurricane risk and coastal regions in the South and Northeast.

Our analysis suggests that NFIP insolvency is driven largely by catastrophic hyperclustering that is not accounted for in the design of the current risk-based premium schemes. In addition, regions with very frequent, recurrent claims that are not always spatially congruent contribute to the NFIP insolvency, and need to be addressed. Our work provides motivation for system intervention under catastrophic hyperclustered conditions and suggests managed retreat for properties exhibiting recurrent losses.

3) Discussion

Using an interdisciplinary approach, we identified hydroclimatic hyperclustering and recurrent losses from high-risk properties as primary insolvency triggers in the NFIP. Although the concept of catastrophic losses and insurance failure has been discussed for years (Kousky & Cooke, 2012), there is less focus upon the components of current disaster insurance systems that work well in contrast to those that create failure. The analysis suggests that with clever reform, the NFIP could be self-sustaining without chronic insolvency, and millions of properties can remain insured for non-hyperclustered flood-related losses. The benefit of retaining a national flood insurance pool diversifies risk sources, and allows for continued insurance coverage for millions of at-risk homes. Here, we suggest that hyperclustered events be insured by a secondary, regionally-funded catastrophe bond to stabilize counties exhibiting extreme expected losses, and that properties with recurrent losses should be given options for managed retreat and removed from the NFIP pool due to the disproportionate strain these properties place on the system. Overall, we find regions most at risk are large, densely populated metropolitan areas with hurricane risk and coastal regions. Our findings spur the following recommendations for NFIP reform:

1) Hyperclustered events should be insured by a secondary catastrophe bond (Braun & Kousky, 2021) or reinsurance mechanism that is triggered by a “hyperclustered threshold” in which the event is too large for normal insurance payout mechanisms.
2) Since failures are not spatially uniform nationwide, targeted efforts to insure hyperclustering must come from local and state governments that are predisposed to these catastrophic risks

in order to incentivize cooperation, widen the insurance pool, and motivate regional risk awareness and accountability.

3) Properties experiencing repeated losses should be given incentives for managed retreat and phased out of the NFIP due to the disproportionate burden these properties place on the system. Programs for public insurance and managed retreat could potentially be linked (Lin, 2024), but must consider systemic incentive structures.

Some recent proposals to fully cancel the NFIP have cited issues of predominantly bailing out waterfront properties of wealthy, high-net worth individuals located in risky areas (Forbes, 2024). However, our evaluation suggests that the dominant source of failure for insolvency and debt is clearly identified as a handful of hyperclustered events, rather than repeated losses. Additionally, our analysis points to the importance of considering spatiotemporally clustered flooding for future insolvency prevention. Conversely, arguments that the NFIP is predominantly serving working-class individuals is also disputed, particularly by scholars studying affordability and uptake (Kousky & Kunreuther, 2014). We note that since identifiable property-level data is not publicly available, we are limited in the scope of analysis of properties with repeated failures to regional aggregation. However, recent investigations of flood insurance claims suggests that only 2.5% of policies result in more than 50% of claims, further underscoring the importance of mitigating high-risk areas (Neptune Flood Incorporated, 2025).

Our work shows that dynamic and flexible risk assessment techniques must evolve to consider the interdisciplinary nature of modern hazard management. In lieu of a static long-term risk assessment (such as the 100-year flood (Bell & Tobin, 2007)) and a short decision evaluation horizon (such as the fiscal year for insurance uptake (Kunreuther & Michel-Kerjan, 2015)), hazard risk management must evolve at flexible temporal scales that reflect changing conditions and risk. Flexible risk assessment must not only include a nonstationary climate (O'Gorman & Schneider, 2009; Pfahl et al., 2017), but also consider population growth in flood-prone regions (Tellman et al., 2021), and more specifically the likelihood of space-time clustering of risk (Bonnafous & Lall, 2021). Natural-human feedbacks must be explicitly considered in our risk modeling processes that include development-protection reinforcing cycles such as the levee effect (Tobin, 1995), land use changes (Rentschler et al., 2023), and catastrophic damage risks (Kousky & Cooke, 2012). We need a more formal consideration of the interlinked decision processes of the insured party, the insurer's risk portfolio, and the regional risk management authority or government regulator. Spatial scale, fiscal health, and risk management capacity need to be considered for the different types of risk exposure and their respective insuring body whether that fall within the private, reinsurance, investor, or public market.

With the majority of insolvency-inducing failures occurring in the 21st century, it remains critical that economists, engineers, and policymakers work together to address threats of hyperclustering in the NFIP. Decadal analysis of regional flood extremes has begun to emerge in hydrologic modeling

(Nayak et al., 2024), but needs to become more standard in building codes and risk assessments. Literature on catastrophe bond design for flooding (Chen et al., 2013; J. Li et al., 2022) and catastrophe reinsurance (Chao, 2021) aims to optimize bond structure and triggers. However, novel design is needed that captures the econometric subtlety of financial markets, the socio-hydrologic dynamics of population migration (Di Baldassarre et al., 2013; Liao et al., 2023; Tobin, 1995), as well as the spatiotemporal hydroclimatic dynamics of flooding (Bonnafous & Lall, 2021). Our study underscores the importance of interdisciplinary approaches to risk quantification. Interdisciplinary studies that aim to inform adaptive planning through multiple vantage points (Edwards et al., 2021; Giang et al., 2015; Nayak et al., 2023) are needed to better address systemic failures in disaster insurance.

Our policy recommendations extend past public insurance pools such as the NFIP and have implications for private disaster markets, such as homeowners insurance, which is experiencing similar hyperclustered stresses from wildfires and hurricane-induced wind-damage (Eaglesham, 2023). Future work aims to investigate the optimization of hyperclustered event thresholds for NFIP policy reform and design robust catastrophe bond triggers for large metropolitan regions with hurricane risk for enhanced disaster resiliency.

4) Methods

4.1) Federal Flood Insurance and Precipitation Data

FEMA provides all redacted flood insurance records publicly through their data portal at OpenFEMA. Our analysis of flood insurance claims includes over 2 million property-level claims and 80 million NFIP policy records, anonymized at the county level, spanning 1978 to 2024, including Risk Rating 2.0 policies (FEMA 2023). We also examine the multiple loss properties database provided by FEMA for properties that have filed repeated NFIP claims. In relation to disaster aid, we analyze Presidential declarations and over 250,000 county-level records of property owner and renter Individual Assistance that amount to millions of household federal aid disbursements. We use the Multi-Source Weighted-Ensemble Precipitation (MSWEP) daily gridded reanalysis data (Beck et al., 2019) for precipitation return periods calculated in (Nayak et al., 2025). CPI-U time series are provided by the US Bureau of Labor Statistics for inflation adjustment.

4.2) Qualitative Synthesis

To understand the status of interactions between US flood insurance mechanisms, infrastructure, and planned relocation efforts in the United States, we conduct a qualitative analysis. We synthesize peer-reviewed literature, technical reports, and policy documents (see SI, Section 1 for a comprehensive list), supplemented with semi-structured interviews with subject matter experts in insurance, government, law, and economics. Detailed information on the interview guide, interviewees, and qualitative data is provided in the SI, Section 1. We combine these qualitative insights and expert perspectives to inform the subjective ranking of insolvency risk measures in the combinatorial game theoretic flood risk weighting, displayed in Figure 6. The expert-informed analysis then allows us to build a foundation on which to ground our analytic approach to investigate potential failure points with big data analytics, and provide practitioner-based risk metrics.

4.3) Spatiotemporal Clustering

As the space-time clustered structure of losses is relevant to both catastrophic extremes and recurrent failures, we employ unsupervised learning to extract spatiotemporal loss clusters from NFIP insurance claim records. DBSCAN (Ester et al., 1996) and its spatiotemporal counterpart ST-DBSCAN (Birant & Kut, 2007) are well-suited for spatiotemporal clustering of extreme weather events (Augenstein et al., 2024; Nayak et al., 2025; Shi et al., 2022). Here we employ ST-DBSCAN to cluster insurance claims data based upon dates of reported loss.

ST-DBSCAN clusters data using an iterative density-based approach in which points within a set space-time threshold are clustered together. The method requires requires three parameters: a space threshold ϵ_S, a time threshold ϵ_T, and $MinPts$, a minimum number of points per "core point", or point that continues the iterative process. The algorithm starts with a random point $i_{x,y,t}$with spatial dimensions x, y and time dimension t. It then examines the nearest neighbors to point $i_{x,y,t}$, and clusters all of those within the Euclidean distance of thresholds ϵ_S and ϵ_T. For clustered neighbor $i'_{x,y,t}$, if there are at least $MinPts$ that are within the specified three-dimensional space-time radius, the algorithm continues with this neighbor and repeats the same process. If there are not, this branch of the iteration stops. Unclustered claims are all assigned to the null cluster (-1).

Previous studies have criticized DBSCAN for its difficulty to parameterize (Schubert et al. 2017). However, in our case, we are able to validate clustering using previously grouped datasets. For disaster aid data, each declaration includes county-level aid eligibility and dates of beginning disaster impact. Thus, presidential disaster declaration numbers provide a natural validation metric. Specifically, we consider a range of $\{\epsilon_T, \epsilon_S, MinPts\}$, then iteratively evaluate the number of disaster declaration numbers that are split across clusters under varying parameterizations. To minimize splitting declarations across clusters, we optimized space, time, and point thresholds, ensuring clusters encompassed entire declarations when possible. We applied DBSCAN under ϵ_T at the county level, followed by ST-DBSCAN for spatiotemporal clustering as seen in (Nayak et al., 2025). A sensitivity analysis assessed cluster characteristics across varying thresholds (see SI, Section 4) and is further detailed in the SI of (Nayak et al., 2025).

4.4) Hotspot Analysis

To perform hotspot analysis across metrics identified through our qualitative synthesis (historic net expected losses, hyperclustered instances, disaster declarations, multiple loss properties, and unclustered claims) we use the Getis-Ord Statistic (Getis & Ord, 1992). The formula for the computation of the standardized z-score Getis-Ord Statistic $G_i *$ is given as follows:

$$G_i * = \frac{\sum_{j=1}^{n} w_{ij}x_j - \underline{X} \cdot \sum_{j=1}^{n} w_{ij}}{s\sqrt{\frac{\left[n\sum_{j=1}^{n} {w_{ij}}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2\right]}{n-1}}}$$

such that $G_i *$ represents the spatial autocorrelation for event i across n events, $\underline{X}$ is the mean, and s is the standard deviation. Here, we implement the Getis-Ord hotspot analysis using Python and geospatial packages pysal and esda across each dataset of interest: 1) expected net losses using Risk Rating 2.0 premiums, 2) count of hyperclustered events per county, 3) count of flood-related presidential disaster aid disbursements per county, 4) count of multiple loss properties by county, and 5) count of unclustered claims per county. We plot the associated Z-scores for significance testing in Figures 2, 5, and 6. Higher Z-scores represent hotspots and lower (negative) Z-scores represent coldspots.

4.5) Game Theoretic Risk Aggregation

To create an aggregate measure of relative insolvency risk considering multiple metrics with varying importance simultaneously (historic net expected losses, hyperclustered instances, disaster declarations, multiple loss properties, and unclustered claims) we employ a game theory-based approach to combine metric weights. In order to aggregate risks spatially across varied metrics using both subjective qualitative-informed and objective weighting mechanisms, we employ game theoretic combinatorial weighting slightly modified from (Lai et al., 2015). We provide a detailing of the abbreviated steps below including our modification. For full analytic derivation we refer to (Lai et al., 2015).

1. *Develop a subjective weighting using our qualitative synthesis.* With our expert interviews and qualitative synthesis we use subjective weighting to rank five metrics: 1) expected loss by county, 2) hyperclustering frequency, 3) disaster declaration frequency, 4) multiple loss property count, 5) unclustered claim count. Then following the Analytic Hierarchical Process (AHP) develop subjective weights for each of the five metrics as shown in (Saaty, 1990).
2. *Develop an objective weighting using the entropy method* (X. G. Li et al., 2012). For n total metrics by m total counties, create b_{ij}, a judgement matrix n by m. Calculate the entropy value H_i and the weight $ew_i$of each county as:

$$f_{ij} = \frac{b_{ij}}{\sum_{j=1}^{m} b_{ij}}$$
$$H_i = -\frac{1}{ln(m)}\sum_{j=1}^{m} f_{ij} \cdot ln(f_{ij})$$
$$ew_i = \frac{1 - H_i}{n - \sum_i^n H_i}$$

3. *Combine subjective and objective weighting using combinatorial game theory.* We now have a set of L weight vectors w_k ={$w_{k1}, w_{k2}, \ldots, w_{kn}$} for n=5 metrics and L=2 weighing mechanisms. The linear combination of the weight vectors is given by $w = \sum_{k=1}^{L} \alpha_k w_k^T, w_k > 0$, and game theory aims to optimize the linear combination coefficient such that the indexes agree best:
$$min \left|\left|\sum_{k=1}^{L} \alpha_k w_k^T - w_i^T\right|\right|_2 \text{ for (i =1,...,L)}$$
To solve this optimization, we take the first order derivative of the matrix $\sum_{k=1}^{L} \alpha_k w_i w_k^T = w_i w_k^T$, then normalize our linear combination coefficient $\alpha'_k = \frac{\alpha_k}{\sum_{k=1}^{L} \alpha_k}$, then calculate the combined weight $w' = \sum_{k=1}^{L} \alpha'_k w_k^T$.

4. *Create and bin counties using categorical threshold grading standards developed with k-means clustering*. We then create n bins using k-means clustering such that *k=n-1* (Macqueen, 1967) to appropriately threshold the bins into different grading thresholds: [lowest, lower, medium, higher, and highest] risk.

Data Availability

All NFIP and disaster data is publicly accessible and can be accessed through FEMA's OpenFEMA portal. All precipitation data can be accessed through GloH2O.

Code Availability

We provide open access code for all processes in this manuscript in the following GitHub repository.

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