

Mapping Flood Memory: How Risk Perception and Social Vulnerability Drive Flood Insurance Patterns in the U.S.

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ABSTRACT

Floods cause severe damage to private property in the United States, but the vast majority of flood-exposed residents are not insured. To gain detailed knowledge on how to improve insurance coverage for people in need, we investigate the temporal dynamics of flood insurance adoption patterns across U.S. counties by analyzing National Flood Insurance Program data through the lens of social memory and risk perception. Using change point detection methodologies, we identify significant shifts in insurance purchasing behavior following flood events and quantify both the magnitude (*salience*) and memory (*time-to-forget*) of these post-flood responses. We show that social memory of flood events, measured through insurance participation rates, may be considerably shorter and more heterogeneous than previously suggested in the literature. By including demographic, environmental, and institutional variables, we disentangle the multimodal distribution of salience and memory. We identify three components driving insurance adoption: social vulnerability, risk perception, and flood damage patterns. Subsequent cluster analysis of these components reveals five distinct county profiles, with notable findings regarding areas where high social vulnerability coincides with low risk perception. The results demonstrate spatiotemporal variations in community responses to flood risks and suggest that only community-specific policy interventions can successfully maintain equitable and sustainable insurance coverage.

1. Introduction

Disasters, particularly floods, pose significant challenges globally, causing loss of life, displacement, and widespread infrastructure damage (Wing et al., 2018, 2020). Flooding stands out as the most frequently occurring natural hazard in the U.S., with rising risks and unequal exposure expected due to climate change (Wing et al., 2022). Even as the threat and financial impact of flooding grow, recent estimates indicate that between two-thirds and 92% of flood-exposed properties are currently uninsured (Choi et al., 2024; CBO, 2024). Understanding local take-up rates and its motivating factors is critical to ensuring equitable flood insurance coverage (Zinda et al., 2022). Identifying drivers of flood insurance uptake provides a basis for strategies to ensure procedural fairness on protection programs, and distributive justice on damage alleviation initiatives (Fleurbaey et al., 2014; Olazabal et al., 2021; Ara Begum et al., 2022).

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40 Access to flood insurance in the United States is regulated by the National Flood Insurance Program (NFIP), a
41 federal government program that provides flood insurance to homeowners, renters, and businesses in participating
42 communities. The program was created by the United States Congress in 1968 to address the lack of flood insurance
43 options in the private market. Its primary goal was to reduce the financial burden on the government from post-flood
44 disaster relief and to internalize the costs of floodplain occupation through flood insurance. This approach aimed
45 to promote the economically efficient use of floodplains while encouraging floodplain management measures for
46 communities (Bin and Landry, 2013).

47 The NFIP program faced initial challenges with low community enrollment levels and low insurance purchase rates
48 by individual property owners in participating communities (Michel-Kerjan and Kousky, 2010). Subsequent legislation
49 was enacted, establishing that property owners residing in 100-year floodplains (also called Special Flood Hazard
50 Areas, SFHA) are bound by federal law to obtain flood insurance if they have a mortgage from a federally regulated
51 or backed lender (called a Mandatory Purchase Requirement, MPR). Regulations also mandate community enrollment
52 as a pre-condition for qualifying for federal disaster assistance on a communal and individual levels. These measures
53 increased the program's impact, with an estimated 22,000 communities benefiting from NFIP coverage nationwide
54 by the end of 2015 (Kousky, 2017). Despite the increase, the current level of flood insurance coverage of the NFIP
55 remains insufficient to reach a balance point in which insurance fees would cover expected flood losses (Gallagher,
56 2014; Kunreuther et al., 2009; Kriesel and Landry, 2004).

57 Due to systemic inequities in flood exposure and post-disaster recovery assistance, floods have intensified pre-
58 existing racial, social, and economic disparities (Zinda et al., 2022). The NFIP plays a critical role in mitigating these
59 inequities by working toward equitable flood insurance access and coverage across the country. Equity can be viewed
60 as a combination of recognitional justice, distributive justice, and procedural justice (Olazabal et al., 2021; Ara Begum
61 et al., 2022). The NFIP would then require policies to address distributive inequities by ensuring fair allocation of
62 benefits and costs, to embrace procedural justice by including vulnerable communities in policy design, and to practice
63 recognition by validating diverse approaches to risk management across different communities (Fleurbaey et al., 2014;
64 Olazabal et al., 2021; Ara Begum et al., 2022). This approach, however, requires a thorough understanding of insurance
65 take-up dynamics at a community level, which remains a gap in the current body of research (Zinda et al., 2022).

66 The insurance program's broad impact and low total coverage have motivated a growing number of researchers to
67 analyze the drivers behind flood insurance demand. There is general agreement on price not being a significant factor
68 shaping insurance take-up due to inelasticity (Atreya et al., 2015; Landry and Jahan-Parvar, 2011; Kriesel and Landry,
69 2004), while variables such as hazard proximity (Kousky, 2010; Zahran et al., 2009; Bin et al., 2008), risk perception
70 (Cannon et al., 2020; Bin and Landry, 2013; Lindell and Hwang, 2008) and demographic characteristics (Lucas et al.,

71 2021; Wang et al., 2017; Landry and Jahan-Parvar, 2011; Michel-Kerjan and Kousky, 2010; Lindell and Hwang, 2008;
72 Browne and Hoyt, 2000) appear to be significant elements driving insurance coverage in the U.S.

73 Several papers show that in the U.S. insurance can be purchased reactively after a flood (Kousky, 2017; Veigel
74 et al., 2023), which is linked to increased risk perception and an overestimation of the probability of a flood shortly
75 after its occurrence (Dumm et al., 2020). Individuals frequently overestimate the likelihood of risks they can easily
76 remember or imagine (Rabin, 1998; Tversky and Kahneman, 1973), which leads to heightened take-up rates shortly
77 after floods that drop back to pre-flood levels over time. Studies characterize both effects as *salience*, measured by the
78 increase in the take-up rate after a flood event, and *memory* or *time-to-forget*, which refers to how long the elevated
79 take-up rates persist following the flood. Kousky (2017) finds that communities that suffered a flood in the previous
80 year increase their net flood insurance purchases by 6.7% and 7.2%, depending on whether a Presidential Disaster
81 Declaration (PDD) was issued. According to her research, this effect disappears three years after the storm. Atreya
82 et al. (2015) finds similar results, stating that the temporary increase in flood insurance purchases after a flood event
83 fades after three years. Studies observe an immediate increase in the number of homeowners who own flood insurance
84 in communities affected by floods. According to Gallagher (2014) and Choi et al. (2024), this effect ranges from
85 7%-9% and then declines steadily to zero nine years after the event. Similarly, while studying the housing market with
86 hedonistic models that explicitly incorporate linear and nonlinear temporal flood-zone effects, Atreya et al. (2013) finds
87 that the flood risk discount disappeared between four and nine years after the flood.

88 While these findings, derived from regression analyses, provide point estimates with confidence intervals, in many
89 cases they rely on the assumption of normally distributed salience and memory effects. Unlike regression-based
90 approaches that assume parametric distributions, change point detection algorithm (CPD) can be implemented with
91 non-parametric methods that detect structural breaks in time series data without imposing distributional assumptions on
92 the underlying process. To advance our understanding of these temporal dynamics, we implement a CPD that allows
93 for an independent quantification of changes in flood insurance coverage for each county. Earlier regression-based
94 studies have highlighted the need to better understand how baseline risk perception and household adaptive capacity
95 influence post-disaster risk perception and subsequent insurance demand. By characterizing temporal changes across
96 different risk and capacity profiles, we establish county-specific baselines that capture the varying risk perceptions
97 that influence post-disaster insurance behavior. Our methodological approach addresses this gap by coupling the
98 CPD results with unsupervised clustering of National Risk Index variables (NRI), enabling us to characterize the
99 heterogeneous distribution of temporal changes in insurance adoption patterns.

100 We analyze over 50 million insurance policies across the Contiguous United States (CONUS) from 2010 to 2021,
101 focusing on the following research questions: (1) how big is the change in insurance uptake after a flood event, measured
102 as a rise in insurance take-up rates (*salience*)? (2) How long does the effect on the insurance market last, following a

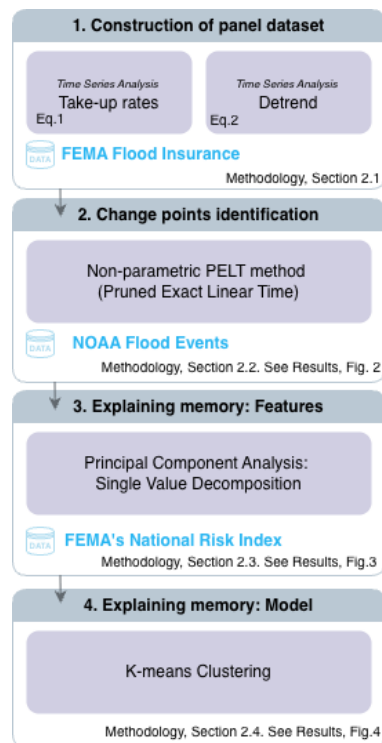


Figure 1: Flowchart summarizing the sequential analysis steps to identify and characterize flood insurance purchasing patterns. Our analysis relies on data from the U.S. National Flood Insurance Program and federal Census Bureau. The first two steps (*Construction of panel dataset* and *Change points identification*) investigate temporal changes in insurance adoption through CPD analysis, validated against NOAA storm and flood event data to identify post-flood salience effects and memory. The bottom panels (*Explaining memory: Features* and *Explaining memory: Clustering*) include feature engineering and cluster analysis incorporating demographic data, NFIP Community Rating System participation, FEMA's National Risk Index (NRI), and Disadvantaged Communities data from the Climate and Economic Justice Screening Tool (CEJST) to identify key predictors of insurance purchasing behavior. Principal Component Analysis and k-means cluster analysis differentiate among patterns in insurance adoption and social memory effects across different U.S. counties. The main data source of each step is reported in the figure, along with a reference to the results relative to each step.

103 flood event until the market returns to initial levels (*memory*)? (3) Which observable characteristics from the counties
 104 under study can explain the variability in memory and salience effects after a flood event? We incorporate the National
 105 Risk Index to address the differences in flood memory and salience resulting from our CPD analysis to uncover patterns
 106 in memory and salience effects. By correlating risk index components with different aspects of flood memory and
 107 insurance adoption patterns, we show how social vulnerability, risk perceptions, and flood damage correlate with
 108 insurance coverage. Our approach helps identify how strategies to counteract the insurance protection gap can be
 109 tailored to the specific characteristics of under protected communities.

110 2. Materials and Methods

111 In this study, we develop a data-driven approach that, in its first phase, analyzes insurance purchase data from
 112 the U.S. National Flood Insurance Program (FEMA, 2023c) in combination with household information from the

113 federal Census Bureau (U.S. Census Bureau, 2022) to identify behavioral patterns of flood insurance purchase through
114 CPD. CPD refers to a set of unsupervised learning techniques that identify critical points in a time series or data
115 sequence where the underlying data distribution changes (van den Burg and Williams, 2022) relative to the time
116 period before the change point. Those are called change points. We compare the timing of the identified change
117 points with the timing of occurrences of storms and flood events, recorded in data from the U.S. National Oceanic
118 and Atmospheric Administration (NOAA, 2023). This comparison allows validating the existence of after-flood
119 salience effects and take-up change duration. A flowchart summarizing the steps included in our analysis is shown
120 in Figure 1. After constructing our input dataset (*Construction of panel dataset* in the figure) and performing change
121 point detection (*Identifying change points*), we perform feature engineering via dimensionality reduction (*Explaining
122 memory: Features*) to recognize a relevant subset of potential predictors from a combination of variables including
123 demographic information from the federal Census Bureau (U.S. Census Bureau, 2018), NFIP participation information
124 from the Community Rating System (CRS) (FEMA, 2021), and natural and social risk information from FEMA's
125 National Risk Index (FEMA, 2023a). We identify the principal components (PCs) affecting salience and memory
126 effects, and group the counties under analysis into clusters with similar insurance purchase and social memory behavior
127 (*Explaining memory: Clustering*). The following sections describe each step of our analysis (Boxes 1-4 in Figure 1) in
128 detail.

129 **2.1. Construction of panel dataset**

130 We analyze household flood insurance purchase data from the United States NFIP, a source of flood insurance for
131 homeowners, renters, and businesses in participating communities mandated by the federal government. The NFIP
132 program maintains a public data source containing over 80 million records of household flood insurance purchases
133 since 1970 (FEMA, 2023c). For this study, we use data comprising over 50 million records ranging from January
134 2010 (the starting point for policy-level data on the current FEMA dataset) until the end of 2021, right before the
135 implementation of pricing changes due to Risk Rating 2.0 (which came into force on April 2022). Regulations mandate
136 individuals to buy flood insurance as a pre-condition for qualifying for federal disaster assistance and when acquiring
137 a governmentally-backed mortgage within the SFHA. The FEMA dataset indicates those conditions with two different
138 data flags, which we used to exclude mandatory purchases due to SFHA and mortgage requirements (12.39% of SFHA
139 policies) and following a PDD (0.28% of SFHA policies). We excluded 3.98 million policies from the analysis to
140 understand policy dynamics beyond mandated purchases, thus restricting it to only voluntarily purchased policies. As
141 a safeguard against potential unobserved mandatory purchases—whether from lender non-compliance or information
142 inconsistencies—we include the county-level SFHA policy ratio as a covariate in subsequent analyses to empirically

143 capture any residual systematic influence. A table showing the data points for each category of exclusion criteria is
 144 shown in Supplemental Material Table 3.

145 We pre-process the data as follows, before feeding them to step 2 of our analysis. First, we spatially and temporally
 146 aggregate the insurance purchase data by adding them up at a county level and with a monthly time-step. This decision
 147 strikes a balance between managing the computational complexity of a country-wide high-resolution analysis and
 148 capturing enough data to have a detailed view of the salience and duration effects. Second, we rescale the insurance
 149 data by the number of households per county from the Federal Census Bureau, and subsequently define our take-up
 150 rate variable $y_{c,t}$ as the net proportion of households that purchased or renewed their flood insurance policies in a given
 151 month t , for a given county c .

152 We thus build a panel of insurance take-up rate signals defined as

$$y_{c,t} = \frac{p_{c,t}}{h_{c,t}}, \quad (1)$$

153 where $p_{c,t}$ is the number of flood insurance policies purchased or renewed in county c during month t , and $h_{c,t}$ the
 154 estimated number of households in county c in month t . As the household information is provided by the federal
 155 Census Bureau every 10 years, we fit a linear interpolation to estimate the monthly number of households per county.

156 Finally, to remove trends from the time series signals, we subtract the take-up rate at time t from the closest
 157 previous element in the series. This results in the detrended take-up rate $d_{c,t}$, formulated as

$$d_{c,t} = y_{c,t} - y_{c,t-1}. \quad (2)$$

158 We analyse these variables as time series and use CPD to find relevant changes in their distributions. We define
 159 the salience as the spike in the insurance take-up—expected to happen shortly after a flood due to increased risk
 160 perception—expressed in percents, and the memory effect as the time it takes for the insurance coverage to drop back
 161 to pre-flood levels, expressed in months. We refer to the time to drop back to pre-flood levels as the “memory effect”
 162 and the “time to forget” interchangeably.

163 Since the objective of our study is to analyze the salience effect on the insurance market after a flood event,
 164 we set minimum thresholds on both the insurance take-up rate at t_0 , i.e., prior to a flood event, and the damage to
 165 infrastructures due to flood events. After conducting a sensitivity analysis (see Table 1 in Supporting Tables), we
 166 define these thresholds to account for 99% of the infrastructural damage in the NOAA database (structural damage
 167 per event higher than USD \$6,000) and 99% of the total insurance policies active during the study period (minimum
 168 initial take-up rate of 0.2%). With those thresholds in place, our study sample consists of a panel of 2055 counties in
 169 the contiguous U.S., corresponding to 65.4% of all U.S. counties. The detrended time series of insurance take-up rate
 170 for each of retained counties comprises 144 data points recorded between January 2010 and December 2021.

2.2. Change points identification

Owing to the high dimensionality of our problem and the need for a tool that is sensitive to short-term variations, we use CPD to analyze the detrended time series of flood insurance take-up rate obtained in the above data gathering and pre-processing step. CPD is the task of (i) statistically determining if there are distribution changes within a signal or time series and (ii) pinpointing the exact locations where changes in distribution occur (Harchaoui et al., 2008). It can be seen as a segmentation exercise, where a full signal y_t is split into segments of similar distribution, delimited by a set of indexes aptly named change points (van den Burg and Williams, 2020). The optimization problem associated with CPD can be generalized as

$$\min_{\tau} \left(\sum_{i=1}^{n-1} C(y_{\tau_i, \tau_{i+1}}) + \lambda P(n) \right) \quad (3)$$

where τ represents a segmentation of the signal, defined by a set of change points $\{\tau_1, \dots, \tau_n\}$. The function $C(y_{\tau, \tau+1})$ represents the cost for each segment of the signal, a measure of disagreement between the data points and a proposed distribution, with negative maximum log-likelihood being one of the most common. $P(n)$ represents a penalty function for the number of segments, and λ stands for the set of hyperparameters used to calibrate said penalty (different methods define λ as a single value or as a complex set of parameters). The risk of overfitting by segmenting the signal into too many parts is balanced by the penalty value and further calibrated by the set of hyperparameters λ . In this way, C , P , and λ become the three fundamental components of any CPD method.

Taking into account previous literature on the comparative performance of known CPD methods (Truong et al., 2020; van den Burg and Williams, 2020; Aminikhanghahi and Cook, 2017), we test a set of six CPD methods with twenty combinations of C , P , and λ parameters. We include in our analysis both parametric approaches - which generally assume normal distribution and independence of the variables in the signal - and non-parametric approaches - which are able to segment a signal with an unknown distribution: Binary Segmentation [BINSEG] (Scott and Knott, 1974) and Pruned Exact Linear Time [PELT] (Killick et al., 2012) as parametric approaches, and Non-parametric PELT (Haynes, Kaylea et al., 2016), Energy Change Point Agglomerative (Matteson and James, 2013), Energy Change Point Divisive (Matteson and James, 2013), and Energy Change Point Divisive on Medians [EDM] (James et al., 2016) as non parametric methods. For more details on the methods see the Supporting Notes - Section 1.3. We then compare the detected change points with the actual flood events data from NOAA (NOAA, 2023). For this comparison, we define a 15-months window after a flood event, in which a change point is considered a true positive. The true positive window is set in that range to capture short-term effects, but considering that flood insurance policyholders tend to let their year-long policies lapse instead of canceling them in mid-duration (Michel-Kerjan et al., 2012). Detailed explanations and mathematical formulations of the selected metrics are described in the Supporting Notes - Section 1.1.

2.3. Explaining memory: Feature Engineering

Following the identification of change points with CPD, we implement Principal Component Analysis (PCA) to reduce the dimensionality of multiple potential flood-related determinants of flood insurance adoption patterns into interpretable components (Jolliffe, 2002). PCA transforms the original n -dimensional data through eigendecomposition of the covariance matrix Σ :

$$\Sigma = V\Lambda V^T \quad (4)$$

where V contains the eigenvectors (principal components (PCs)) and Λ contains the eigenvalues representing the variance explained by each PC. Each PC is constructed as a linear combination of the standardized original variables:

$$PC_i = \sum_{j=1}^n w_{ij}x_j \quad (5)$$

where w_{ij} represents the loading of variable j on principal component i , and x_j is the standardized transformation of the original j -th variable. As an output of this dimensionality reduction step, we obtain the set of numerical weights, representing the relative contribution of each input variable on the resulting principal components. The input variables are CRS participation, CRS class rating, NRI risk score, NRI resilience score, NRI social vulnerability score, NOAA yearly average events, NOAA average yearly damage, CEJST disadvantaged population, NFIP initial take-up, and NFIP SFHA policy ratio. NRI resilience score, NRI risk score, and NRI social vulnerability score were extracted from FEMA's National Risk Index (NRI) data (FEMA, 2023b). CRS participation and CRS class rating were derived from FEMA's NFIP Community Status Book (FEMA, 2021). CRS participation is the percentage of communities participating in the CRS relative to the total number of communities in each county, the CRS class rating is calculated as the average class rating associated with all policies in the county. Disadvantaged population percentage is extracted from the Climate and Economic Justice Screening Tool - Council on Environmental Quality (on Environmental Quality, 2024). NOAA yearly average events and NOAA average yearly damage are aggregated based on the NOAA flood data (NOAA, 2023). NFIP initial take-up and NFIP SFHA policy ratio are calculated based on the NFIP policy data, with the NFIP SFHA policy ratio defined as the county-level proportion of flood insurance policies located within Special Flood Hazard Areas relative to all policies in that county. As noted in Section 2.1, this last variable also serves as a safeguard to empirically capture any residual systematic influence of unobserved mandatory purchases.

2.4. Explaining memory: Clustering

In order to identify distinct patterns in county-level flood response characteristics, we implement k-means clustering (Lloyd, 1982). We base the clustering on the principal components (PC1-PC3), the response variables *salience* and *memory*, and cluster coastal and inland counties separately. The k-means algorithm partitions counties into a predefined set of k clusters by minimizing the within-cluster sum of squares. We determine the optimal number of clusters k by

228 using the elbow method (Thorndike, 1953) and specifying a minimum cluster size to ensure relevance for policy
 229 makers. The corresponding results for different values of k are shown in Supporting Figure 3. The selected amount of
 230 clusters (k) maximizes interpretability while maintaining clear separation between coastal and inland counties.

231 3. Results

232 The set of counties shown in Figure 2 (top map) represents the working sample of counties retained after
 233 establishing the minimum thresholds for damage and take-up rate. This working sample of 2055 counties covers all 48
 234 states in the Contiguous U.S. It contains representative samples from coastal and inland territories alike, and different
 235 levels of flood risk as measured by the SFHA risk indicator.

236 3.1. CPD Results

237 The metrics and performance evaluation of the CPD method is described in detail in the Supporting Notes - Section
 238 1.1. The Recall metric represents the number of identified change points that match with a flood event from the NOAA
 239 database, where damage to infrastructures is higher than zero. We defined non-parametric PELT (Killick et al., 2012)
 240 as the best-fit method for our study, based on a combination of performance metrics including Recall, Precision,
 241 Annotation error, and Hausdorff distance. In our study, the PELT CPD method's Recall indicates that 30.61% of the
 242 change points in the take-up rate time series overlay with a damage-inducing flood event (see Supporting Information
 243 Table 2). Moreover, 1374 of the 2055 counties in the sample (66.86%) have *at least one* flood event which co-occurs
 244 with a detected change point in the take-up rate signal (see Table 1). The remaining change points could be related to
 245 local reforms, CRS efforts, or media attention, however identifying these factors falls beyond the scope of our study.
 246 The full results of the CPD methods performance test can be found in the Supporting Information Figure 1.

247 For the counties and flood events with an increase in the insurance uptake after a flood event (992 counties, 48.27%),
 248 we proceed to analyze if and how long it takes for their memory effect to wear out. Figure 2 presents the results of
 249 the analysis, where we find 773 counties (37.62%) where a flood event is followed by an increase in the take-up rate
 250 and then a drop back to base levels. These counties exhibit a mean time-to-forget of 25.3 months (i.e., 2.1 years) and
 251 a median of 16 months (1.3 years).

252 The top map in Figure 2 displays the average flood salience effect across U.S. counties on a simplified three-level
 253 scale (low to high), discretized by number of observations (Low: 0% to 2.7% take-up rate, Mid: 2.7% to 10.8%, High:
 254 over 10.8% take-up rate). The map reveals significant spatial variation in insurance salience. Regions characterized
 255 by high flood insurance coverage, such as Florida and the Pacific Coast, exhibit low salience. Conversely, the most
 256 pronounced salience responses in our sample occur in regions with low flood insurance take-up rates, including major
 257 river systems like the Mississippi. The accompanying histograms show the distribution of the flood memory effect

Table 1

Descriptive statistics of CPD results and sample of U.S. counties considered for CPD in our analysis.

Descriptive statistic	Value	Relative Percentage
Total Counties in sample (n)	2055	100.00%
Counties with positive recall (n)	1374	66.86%
Counties with salience effect (n)	992	48.27%
Counties with memory effect (n)	773	37.62%
Salience mean (%)	15.01	
Salience median (%)	7.29	
Salience std. dev. (%)	23.51	
Memory mean (months)	25.3	
Memory median (months)	16	
Memory std. dev. (months)	23.98	

(ranging to 120 months) and flood salience (measured as percentage change). A detailed highlight of the selected case study of Suwannee County, Florida, showcases a typical pattern of temporal dynamics of insurance take-up rates, showing distinct change points following flood events and a characteristic *time-to-forget* pattern where insurance participation gradually declines.

Given the skewed distribution of memory and salience shown in the histograms in Figure 2, the mean values of salience and memory alone do not capture the heterogeneity of flood insurance uptake and memory across different counties. In the next sections, we disentangle the distribution of memory and salience with additional data, which will allow us to identify and characterize different demographic and risk indicators.

3.2. PCA revealing heterogeneous flood insurance take-up characteristics

We use Principal Component Analysis (PCA) to reduce the dimensionality of potential flood insurance determinants into three orthogonal components, which together explain 55.97% of the variance in the data (see Supporting Figure 2). These components represent distinct, composite profiles that drive insurance adoption patterns (Figure 3 (A)). Note that the sign of principal component scores is arbitrary. We have oriented them so that a positive score on a given PC corresponds to a higher expression of the core variables that characterize that profile.

The first component (PC1) defines a *social vulnerability profile*, characterized by high positive loadings on the NRI Social Vulnerability score and CEJST Disadvantaged Population percentage, and a strong negative loading on the NRI Resilience score. Counties with high positive scores on PC1 are those with greater socioeconomic disadvantage and lower institutional resilience.

The second component (PC2) defines a profile of *risk perception* and insurance engagement. It is heavily weighted by high NFIP initial take-up rates, better CRS class ratings (indicating active community-level risk management), and higher NRI Risk scores. These observed metrics can be interpreted as proxies for revealed risk perception. Risk perception is represented as four dimensions: perceived likelihood of occurrence (NRI Risk score), severity of personal

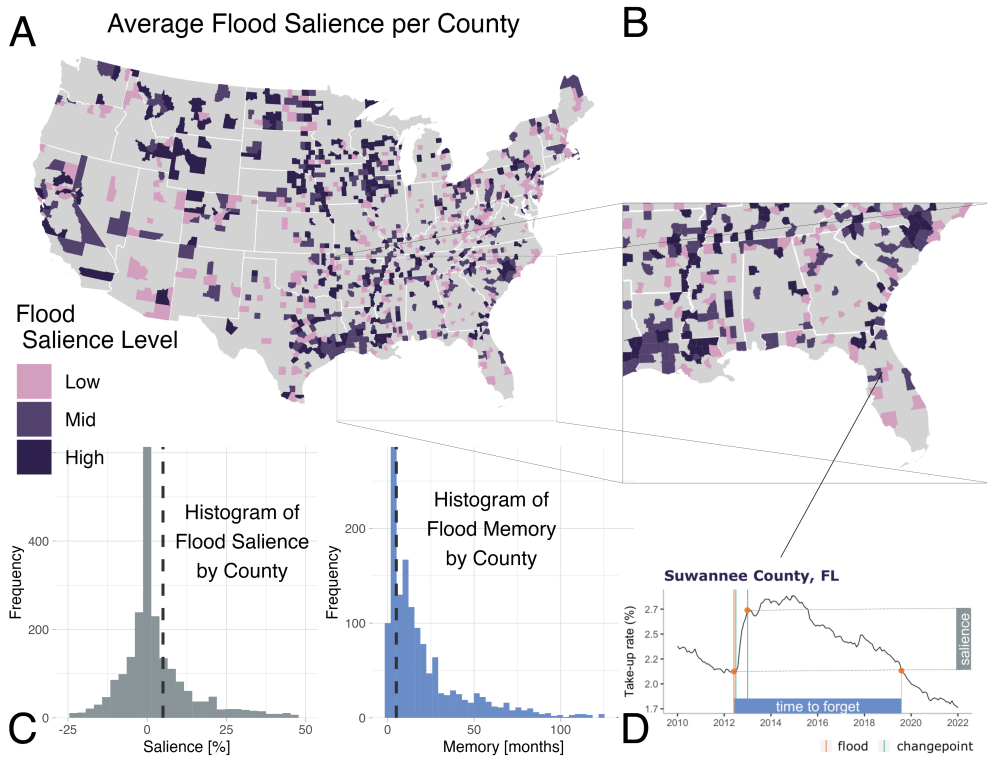


Figure 2: Analysis of flood salience and memory across a sample of 2055 U.S. counties, selected based on threshold criteria of damage and flood insurance take-up rates. The map in panel A, top-left, shows the geographical distribution of three levels of salience effects (low, mid, high), indicated with different colors. The zoom window in panel B shows the geographical distribution of memory and salience in the southeastern coast. A corresponding frequency distribution of the salience and memory variables by county are represented in the two histograms below the map (panel C). As an example, Suwannee County in Florida is selected to illustrate the temporal evolution of flood insurance take-up rates in a high salience county (panel D). The identified change points are marked as orange dots in the timeline and the flood occurrences are indicated as green vertical lines.

280 impact (Flood insurance take-up rate), information from authorities (Social vulnerability score), and consequences for
 281 others (CRS class rating) (Paniello-Castillo et al., 2025a,b; Dryhurst et al., 2020; Leiserowitz, 2006). Representing
 282 perceived likelihood, worry and social dimensions of risk perception in this study is more robust than a single value
 283 indicator (Leiserowitz, 2006). Communities that are better informed about flood risk through official channels and have
 284 a lower social vulnerability tend to exhibit higher risk perception, since they have a higher response capacity and the
 285 possibility to share relevant information. CRS class rating reflects the degree to which a community has collectively
 286 invested in flood mitigation measures; higher ratings indicate broader community-wide risk reduction efforts, meaning
 287 that active CRS participation generates shared benefits that lower flood consequences for all residents, not only those
 288 holding insurance policies. Counties with high positive scores on PC2 are those with greater baseline flood insurance
 289 coverage, more active community risk management (CRS), and higher institutional risk overall (besides flood alone).

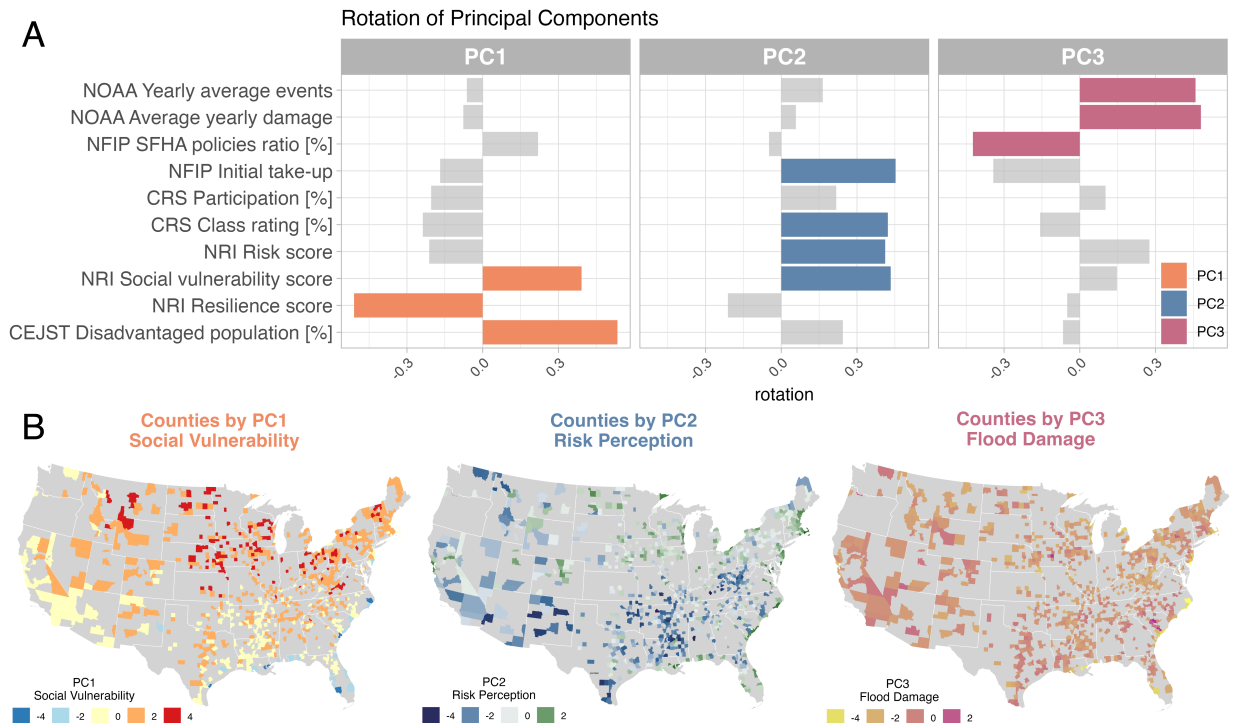


Figure 3: The top panel (A) shows the loadings of input variables on the first three principal components (PCs). PC1 corresponds to a *social vulnerability profile*, indicated by high positive loadings on disadvantaged population percentage and social vulnerability score, and a high negative loading on resilience score. PC2 corresponds to a *risk perception and flood insurance engagement profile*, with strong positive loadings on NFIP initial take-up rates, risk and social vulnerability scores from the National Risk Indicator, and class rating from the Community Rating System. PC3 corresponds to a *flood damage profile*, with high positive loadings on average yearly damage, event frequency, and a negative loading on the ratio of NFIP policies within Special Flood Hazard Areas (SFHA). Panel (B) maps the PC scores for each county, revealing distinct spatial patterns: counties with positive PC1 scores (social vulnerability profile) cluster in the north/northeast; counties with negative PC2 scores (low risk perception and flood insurance engagement profile) dominate the southwest and Mississippi River region; and PC3 scores (damage profile) show a heterogeneous distribution nationwide.

290 The third component (PC3) defines a *flood damage profile*, dominated by high positive loadings on average yearly
 291 flood damage and event frequency. A notable negative loading on the ratio of NFIP policies within Special Flood
 292 Hazard Areas (SFHA) indicates that in counties with high PC3 scores, a significant portion of insurance purchases
 293 occurs outside officially designated high-risk zones, suggesting either localized risk awareness or limitations in current
 294 floodplain mapping. Counties with high positive scores on PC3 are those with greater historical flood damage and event
 295 frequency, especially that occurring outside of mapped high-risk zones (SFHA).

296 The corresponding maps in Figure 3 (B) show the geographical distribution of PC scores for each county. This
 297 reveals distinct spatial patterns: counties with positive scores on the social vulnerability profile (PC1) are concentrated
 298 in the north and northeast, those with positive scores on the risk perception profile (PC2) are prominent across the
 299 south and southeast, and the flood damage profile (PC3) shows a more heterogeneous distribution across the United

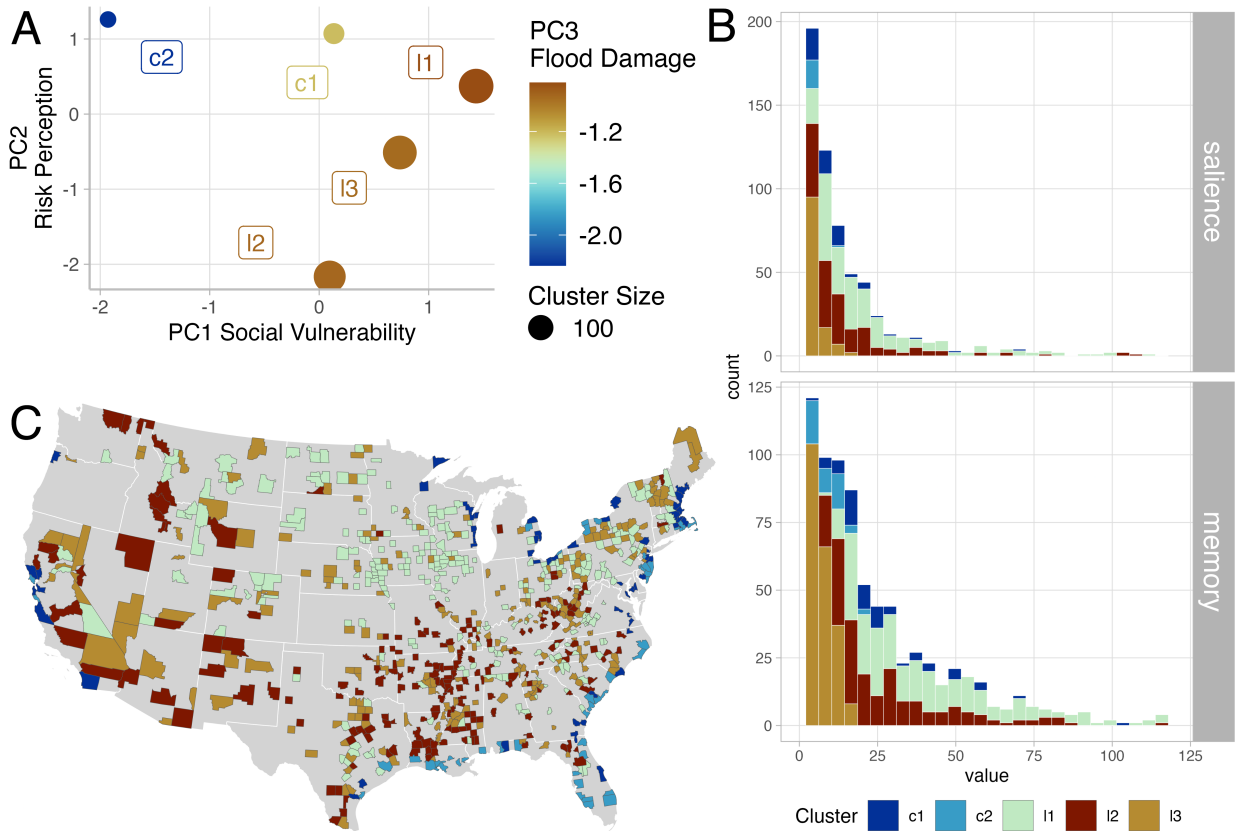


Figure 4: The scatter plot (A) shows clustering results. The clustering shows groupings of counties with similar characteristics, particularly distinguishing between coastal counties with high risk perception (*c1*, *c2*) and inland counties with lower flood risk perception (*l1*, *l2*, *l3*). Counties with both high social vulnerability and high risk perception (clusters *l1* and *c1*) will respond with a high salience and long memory to flood events, while counties with a lower risk perception and higher social resilience tend to respond with lower salience and short flood memory (clusters *l2* and *l3*). Clusters are shown on the map (C) to verify geographical patterns. In the histograms in the right panel (B) the clustering is mapped onto the salience and memory effects.

300 States. These spatial patterns raise the question of how the components interact to form distinct county-level response
 301 types, i.e., how they relate to different patterns of flood insurance salience and memory.

302 3.3. Disentangling the memory and salience distribution with cluster analysis

303 The clustering analysis presented here synthesizes the previous findings through grouping counties based on our
 304 response variables (*salience* and *memory*), our independent variables grouped into principal components (*PC1*, *PC2*,
 305 and *PC3*), and the categorical binary variable *coastal*, which indicates whether a county is on the shoreline. The
 306 clustering results are then mapped onto the histograms of memory and salience to evaluate the connection between
 307 the identified clusters and the distributions of salience and memory. Our cluster analysis results in the identification of
 308 $k=5$ different clusters of counties, which exhibit different salience and memory effects, each characterized by different

309 combinations of PCs and coastal/inland communities. The scatter plot in Figure 4 (A) shows these five resulting distinct
 310 clusters, each further detailed with descriptive statistics in Table 2.

311 Overall, trade-offs between the principal component profiles emerge for clusters *c1*, *l2*, and *l1*. Not all communities
 312 with a strong social vulnerability profile (positive PC1) exhibit a strong risk perception profile (positive PC2), and
 313 neither show a clear correlation with a high flood damage profile. Clusters *c1* and *c2* include coastal counties,
 314 characterized by a stronger risk perception profile than their inland counterparts in clusters *l1*, *l2*, and *l3*. Counties
 315 in *c2*—mostly found in Florida, the Gulf of Mexico, and the southern Atlantic coast—exhibit the most pronounced
 316 risk perception profile, marked by high initial take-up rates, high risk scores, and high community class rating. The
 317 counties in this cluster present a low salience effect of 1.97%, and a short memory effect of 8.43 months on average,
 318 which can be due to these markets having a significantly higher flood insurance penetration of 19.91% initial take-up
 319 rate, compared to a 1.59% on average for inland counties. Meanwhile, *c1* includes coastal counties with a moderate
 320 social vulnerability profile (PC2), mostly located on the north-Atlantic coast and the Great Lakes. This group shows
 321 a similar risk perception profile to *c2*, but a relatively high salience effect after flood events with a median impact
 322 of 11.28% and a memory effect of 26.88 months on average. These results indicate a reactive yet long-lasting flood
 323 insurance take-up behavior (once a flood insurance is purchased, it is retained for longer time than the average for all
 324 data points combined). Both coastal clusters show lower PC3 scores than inland counties, but differ markedly from
 325 each other. Since *c1* and *c2* share similar coastal flood exposure, the gap in PC3 scores (−1.22 vs. −2.24) is primarily
 326 driven by differences in SFHA policy ratio. The more negative PC3 score in *c2*, reflecting a higher SFHA policy ratio,
 327 indicates an insurance market well-aligned with mapped risk areas, where compliance with the mandatory purchase
 328 requirement or risk-aware voluntary adoption may sustain high baseline coverage and dampen post-flood salience.
 329 Conversely, *c1*'s less negative PC3 score points to more insurance activity outside mapped zones, leaving households
 330 more susceptible to reactive uptake.

331 When it comes to inland counties, the *l1* cluster shows similar characteristics to *c1* in terms of reactive behavior:
 332 a combination of high social vulnerability scores and a strong risk perception profile (i.e., high NFIP participation),
 333 paired with a very strong salience effect when hit with a flood event. Mostly located in the area of the Midwest and
 334 Great Lakes towards the Mid-Atlantic, the *l1* cluster shows the highest average after-flood effects in our sample, with
 335 an average impact of 25.25% and an average memory of 42.64 months. Cluster *l2* stands at the opposite end of the
 336 spectrum with low values in both PC1 (social vulnerability profile) and PC2 (risk perception profile), its counties mostly
 337 located in the deltas of main rivers like the Mississippi, Colorado, and Columbia. This cluster's behavior resembles
 338 *c1* in showing a 14.77% salience effect and an average memory of 28.31 months. Lastly, cluster *l3* is characterized by
 339 centered values in all three PCs, and does not show a defined geographical pattern. Despite its moderate profile, both

Table 2

Descriptive statistics from cluster analysis and resulting insurance take-up rate salience and memory effects organized by cluster.

Cluster	c1	c2	l1	l2	l3
Cluster type	coastal	coastal	inland	inland	inland
Counties in cluster (n)	59	47	247	192	228
Avg. initial take-up rate (%)	3.73	19.91	1.4	1.65	1.74
PC1: Social Vulnerability (index)	0.13	-1.93	1.43	0.1	0.74
PC2: Risk Perception (index)	1.07	1.26	0.37	-2.16	-0.51
PC3: Flood Damage (index)	-1.22	-2.24	-0.82	-0.92	-0.93
Salience mean (%)	11.28	1.97	25.25	14.77	3.02
Salience median (%)	7.76	1.01	16.16	9.72	2.21
Salience std. dev. (%)	12	2.17	28.25	17.36	2.87
Memory mean (months)	26.88	8.43	42.64	28.31	7.03
Memory median (months)	21	8	35	21	6
Memory std. dev. (months)	18	5.28	27.16	19.66	3.48

in terms of social resilience and NFIP participation, the counties in *l3* exhibit the lowest post-flood response among inland clusters, with a 3.02% average impact measure and a short average memory of only 7.03 months.

4. Discussion and Policy Implications

In this study, we analyze over 50 million records of household flood insurance purchase across the Contiguous U.S. from 2010 to 2021 and contribute a data-driven framework based on CPD, dimensionality reduction via PCA, and clustering to identify heterogeneous flood insurance purchase patterns for U.S. counties, along with their salience and memory effects. Our findings demonstrate that household responses to flood events through insurance adoption are characterized by both heterogeneous magnitude (salience) and duration (memory). This temporal pattern suggests a significant challenge in maintaining equally distributed flood insurance uptake in long-term flood resilience through voluntary insurance programs.

Flood events trigger a median increase in insurance uptake of 7.29%, with an average increase of 15.01% (Table 1). This salience effect is short-lived: the average "time-to-forget" is 25.3 months, with a median of only 16 months. These findings indicate a shorter social memory than the 3–9 years reported in prior literature (Kousky, 2017; Atreya et al., 2015; Gallagher, 2014), while confirming the reactive nature of flood insurance purchases (Gallagher, 2014; Kousky, 2017). The higher-than-expected salience versus previous studies (Kousky, 2017; Atreya et al., 2015; Gallagher, 2014; Choi et al., 2024) may result from our exclusion of mandatory policies, which exhibit minimal behavioral response and would otherwise dilute estimates. Furthermore, the high standard deviations (Table 2) underscore that salience and memory are highly heterogeneous effects, with national and state-level analysis masking profound disparities in how communities experience and prepare for floods.

359 We address the gap in identifying drivers of the heterogeneous distribution of flood insurance memory and salience.
360 We show that counties with a stronger risk perception profile—reflected in higher baseline insurance engagement—tend
361 toward proactive insurance uptake (clusters *c1* and *c2*). This aligns with findings that perceived future damage reliably
362 predicts insurance take-up (Landry and Turner, 2020). Counties combining high social vulnerability with a strong
363 risk perception profile (clusters *11* and *c1*) show the most pronounced reactive responses: high salience and long
364 memory effects. This suggests flood events effectively actualize latent risk perception. These clusters also unite high
365 vulnerability with low initial take-up rates, consistent with research linking underinsurance to lower income and larger
366 minority populations (Amornsiripanitch et al., 2025). In contrast, counties in lower social vulnerability clusters (*12*, *13*
367 and *c2*) exhibit comparatively lower salience and shorter memory effects.

368 Additionally, we find a group of 154 inland counties (cluster *13*) that, despite showing moderate level of risk
369 perception, low NFIP participation, and social resilience, exhibit a minimal reactive response to floods with a 3.02%
370 average impact measure and a short average memory of only 7.03 months. In these areas, insurance is usually taken up
371 after the event and drops quickly with a return to the low pre-flood levels, leaving these areas vulnerable to experience
372 uninsured losses. We find no evidence that this reactive behavior is due to affordability issues, since clusters with
373 higher social vulnerability (cluster *12*) show higher salience and longer memory effects. This group exhibits behavior
374 consistent with previous literature, where the flood damage risk gets discounted based on the relative infrequency of
375 flood events (Dumm et al., 2020).

376 Achieving equitable flood insurance coverage requires policies that address distributive justice, procedural justice,
377 and recognitional equity (Fleurbaey et al., 2014; Olazabal et al., 2021; Ara Begum et al., 2022). Our clustering analysis
378 reveals systematic disparities in how communities experience and respond to flood risk, raising questions of justice in
379 disaster preparedness and recovery. Specifically, the emergence of social vulnerability (PC1) and risk perception (PC2)
380 as independent principal components points to a recognitional inequity: communities' vulnerabilities in clusters *11* and
381 *13* are not adequately acknowledged in risk communication and flood insurance promotion. The double issue of high
382 social vulnerability and high flood damage for counties in clusters *11* and *13* demonstrates distributive inequity where
383 vulnerable populations face compounded disadvantages.

384 Overall, the clustering results demonstrate substantial heterogeneity in flood insurance purchase behaviors
385 across counties, suggesting that a one-size-fits-all approach to flood insurance policy may be suboptimal because
386 it fails to address the distinct risk profiles and behavioral responses—such as variations in salience, memory, and
387 vulnerability—characteristic of each cluster. Consequently, policy interventions must be calibrated to these local
388 profiles to be effective and equitable. Our results show that structural reforms are needed to ensure accurate mapping
389 for the SFHAs. PC3's inverse relation between flood damage and SFHA policy ratio suggests that current SFHA
390 delineations fail to fully capture risk, consistent with previous findings (Noonan et al., 2022; Pollack et al., 2023).

391 Counties with high flood damage but low SFHA policy ratios—where insurance activity concentrates outside mapped
392 zones—could serve as markers for under-mapped areas requiring revised floodplain designations. This pattern also has
393 implications for the mandatory purchase requirement: in cluster *c2*, the high SFHA policy ratio aligns with low salience
394 and high baseline coverage, consistent with the SFHA policy ratio capturing residual effects of mandatory purchases
395 as described in Section 2.1. In contrast, cluster *c1* combines a lower SFHA ratio with reactive insurance behavior
396 (11.28% salience) and a baseline take-up of only 3.73%. The median insurance coverage in 2010 was higher than in
397 2021, with a significant negative trend over the study period that disproportionately affects these already vulnerable
398 coastal populations, widening the protection gap where adaptive capacity is lowest.

399 Our cluster profiles provide the empirical foundation for a differentiated policy approach. Cluster *l3* is characterized
400 by inland counties with moderate vulnerability and a low risk perception profile (228 counties). Here, the short memory
401 of 7 months can be addressed with sustained interventions consisting of bi-annual campaigns to increase renewals.
402 Given the 7-month memory effect, mandatory outreach at 6, 12, and 18 months post-flood could be implemented, not
403 just annual reminders. Our findings suggest that waiting for annual renewal cycles misses the decay curve of event
404 salience. Cluster *l1* has a high vulnerability, high salience, and long memory in inland counties (247 counties). These
405 Midwest and Mississippi counties show the strongest reactive response and longest memory (25.5% salience, 45.6-
406 month memory) but lowest baseline coverage (1.4%). Since these areas show high reactivity, policymakers can invest
407 in regional flood event publicity and risk awareness to trigger insurance uptake even in non-directly-affected counties.
408 Cluster *c2* shows low vulnerability, high risk perception in coastal counties (59 counties). These counties have the
409 highest baseline coverage (19.91%) but the shortest memory (8.43 months), the lowest salience (1.97%), and low flood
410 damage, suggesting market saturation and potential complacency. However, affordability should be closely maintained
411 and engagement in the CRS should be further encouraged in these areas. Finally, coastal cluster *c1* is defined by low
412 vulnerability and high risk perception. These communities can sustain actuarially fair premiums given their lower
413 vulnerability and longer memory effects.

414 Several methodological constraints should be considered when interpreting our results. First, the county-level
415 aggregation of flood experience may mask significant within-county variations in direct flood exposure, a limitation
416 also described by Choi et al. (2024), who note that this aggregation could potentially underestimate the insurance
417 response among directly affected households.

418 Second, in this study we primarily focus on the effects of direct flood experience while disregarding the potential
419 influence of proximity effects, such as floods occurring in nearby counties or the influence of social networks. Previous
420 research has analyzed social and geographical proximity effects with positive results (Gallagher, 2014; Hu, 2020, 2022).
421 Disregarding these effects might negatively influence our evaluation of change point detection methods, particularly
422 the precision and recall metrics, as some real effects might have been incorrectly considered “false positives.”

423 Despite these limitations, our large-scale data-driven analysis provides a robust evidence base to counteract reactive
424 insurance uptake. Proactive insurance uptake with policies that are held on for long times present a more sustainable
425 adaptation choice resulting in higher community resilience. For instance, our findings on short memory duration
426 suggest that extending policy terms or aligning communication with local memory decay curves could improve long-
427 term coverage. Furthermore, identified clusters provide a quantitative basis for designing equitable insurance access
428 and targeting interventions to the communities that would benefit the most. Future research should build on this
429 foundation by evaluating targeted risk communication strategies and further investigating the drivers of insurance
430 purchase behavior at community level.

431 5. Conclusion

432 This study demonstrates that flood insurance adoption in the United States follows heterogeneous temporal patterns
433 characterized by reactive purchasing after flood events and relatively short social memory. Through change point
434 detection analysis of over 50 million NFIP policies from 2010-2021, we find that post-flood insurance uptake increases
435 by an average of 15.01% (median 7.29%), but this effect dissipates within an average of 25.3 months—substantially
436 shorter than the three to nine years reported in previous literature. Our principal component analysis reveals three
437 independent dimensions driving insurance behavior: social vulnerability, risk perception, and flood damage patterns.
438 Critically, risk perception operates independently from actual flood damage, indicating that individual insurance
439 decisions often diverge from objective risk. The resulting cluster analysis identifies five distinct county profiles with
440 markedly different responses to flood events, demonstrating that a one-size-fits-all policy approach fails to address the
441 diverse needs across communities. The identified clusters expose systematic variations in flood insurance coverage.
442 Counties with high values in social vulnerability and risk perception components (clusters *11* and *c1*) demonstrate
443 strong reactive responses with long memory effects, yet maintain low baseline coverage rates. Meanwhile, moderately
444 vulnerable inland counties with low risk perception (cluster *13*) exhibit minimal response to flood events, suggesting
445 systematic underpreparedness that cannot be attributed solely to affordability constraints. These patterns highlight the
446 need for differentiated policy interventions tailored to each cluster's specific characteristics. Our findings underscore
447 that only community-specific approaches, addressing distributive justice, procedural inclusion, and recognitional equity
448 can effectively ensure resilient and equitable flood risk management across diverse communities.

449 Software and Data Availability Statement

450 The data used in this study is openly available from the cited sources. The R Code used to perform the analysis is
451 available upon request.

CRediT authorship contribution statement

Eric Contreras: Conceptualization, Methodology, Software, Validation, Formal Analysis, Resources, Writing - Review & Editing. **Nadja Veigel:** Conceptualization, Methodology, Software, Validation, Formal Analysis, Resources, Writing - Original Draft, Writing - Review & Editing. **Jacek Suda:** Writing - Review & Editing, Supervision. **Heidi Kreibich:** Writing - Review & Editing, Supervision. **Andrea Cominola:** Conceptualization, Methodology, Funding Acquisition, Project Administration, Writing - Review & Editing, Supervision.

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