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Flood Risk Behaviors of US Riverine Metropolitan Areas are Driven by Local Hydrology and Shaped by Race

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Abstract

Flooding risk results from complex interactions between hydrological hazards (e.g. riverine inundation during periods of heavy rainfall), exposure, vulnerability (e.g. the potential for structural damage or loss of life), and resilience (how well we recover, learn from, and adapt to past floods). Building on recent coupled conceptualizations of these complex interactions, we characterize human-flood interactions (collective memory and risk enduring attitude) at a more comprehensive scale than has been attempted to date across 50 United States metropolitan statistical areas with a socio-hydrologic (SH) model calibrated with accessible local data (historical records of annual peak streamflow, flood insurance loss claims, active insurance policy records, and population density). A cluster analysis on calibrated SH model parameter sets for metropolitan areas identified two dominant behaviors: 1) “risk enduring” cities with lower flooding defenses and longer memory of past flood loss events, and 2) “risk averse” cities with higher flooding defenses and reduced memory of past flooding. These divergent behaviors correlated with differences in local stream flashiness indices (i.e. the frequency and rapidity of daily changes in streamflow), maximum dam heights, and the proportion of white to non-white residents in US metropolitan areas. Risk averse cities tended to exist within regions characterized by flashier streamflow conditions, larger dams, and larger proportions of white residents. Our research supports the development of socio-hydrologic models in urban metropolitan areas and the design of risk management strategies that consider both demographically heterogeneous populations, changing flood defenses, and temporal changes in community risk perceptions and tolerance.

Significance Statement

Flooding remains one of the costliest natural disasters globally. Perceptions of- and strategies for mitigating-riverine flooding risk vary both within and across communities, yet this is often overlooked in formal planning efforts. We fit a socio-hydrologic model to 50 US metropolitan areas to understand divergent community risk behaviors. We identified two archetypes: “risk-enduring” communities with lower flood defenses and longer memory of past floods, and “risk averse” communities with higher defenses but shorter memory. Behaviors were correlated with streamflow conditions, local dam heights, and the proportion of white to non-white residents. Our findings highlight a potential awareness of local hydrology that may drive perceptions of risk as well as racial inequity in flood exposure and resilience within the US.

Main Text

1. Introduction

Global annual riverine flooding losses are projected to rise from 45 billion USD in 2019 to 535 billion USD by 2050(1). Annual average flooding losses across the US rose from 1.1 billion USD in the 1980s to 4.92 billion USD in the 2010s(2). While some increase in loss can be attributed to the increasing frequency and intensity of storms, the risk posed by flooding is a complex interaction between riverine inundation, exposure and vulnerability (e.g. the potential for structural damage or loss of life), and resilience (how well we can recover, learn from, and adapt to past floods)(3). Mitigation strategies that focus exclusively along one dimension of risk (e.g. levee construction to reduce exposure to riverine hazards(4)), might change human perceptions and behaviors in ways that increase the long-term risks of communities (e.g. through reduced memory of past flooding)(5).

Minimization of flooding risk requires that mitigation practices account for physical hazards, community vulnerabilities, perceptions held by at-risk populations(6–8), and trust between the public and decision makers(9).

Strategies for mitigating flooding risk vary within and across communities(10, 11), and are mediated by the political institutions and economic interests that dominate local decision-making around land use and real estate development(12). Prior research has characterized flood mitigation practices as either being "green", for managing their hazards through migration, or "technological", reliant on flood control infrastructure for risk mitigation(13). Satellite nighttime light data provides some evidence that these divergent strategies are both globally ubiquitous (14). Within the US, both strategies are used in formal flood control practices. The US Flood Control Act of 1936 authorized federal capital investments in flood control such as the construction of levees and dams to reduce community exposure, while facilitating continued economic development(15). Buyout programs authorize the use of pooled resources to relocate at-risk residents, yet this functions occasionally as an unevenly used mechanism of flood migration in the US due to political projects misaligning with social movements (16–18). Within the limits of state regulations, individuals can manage their risk independently of their community through the purchase of optional supplementary flood insurance policies, by choosing how to rebuild in-place following disasters, or by migrating. Globally, flood perceptions(19–21), vulnerabilities (22), and approaches to exposure management (11) vary based on sociodemographic factors and public policies.

One possible explanation for these variations is that individual residents and empowered decision-makers (e.g. policy-makers, real estate developers, and lenders) vary in their awareness of hydrology and its potential socioeconomic impacts (e.g. flooding leading to health and economic losses), or in their prioritization of hydrologic risks(23). Experience with floods may increase homeowner's perceptions, preparedness, and risk tolerance(7), but only as long as communities retain "memories" of past events(24). Community memory (i.e. sustained community-scale behaviors in response to an environmental stimuli) can be altered through various mechanisms such as the salience of the literal memories of living witnesses(23), emigration of experienced residents and migration by those with less local flood knowledge(25), land use change in flood-prone regions(26), and publication of floodplain maps(27). Flooding may lead to migration from floodplains, yet populations may return within a decade(25) when the memories of living witnesses in flood prone regions are lost across generations(23). Take-up rates in flood insurance programs tend to increase after catastrophic flooding events, and then lapse during periods of calm(10, 28). Taken together, this evidence suggests that communities lose their risk-awareness over time during periods of calm, and highlights that in the absence of new or strengthened regulations, or where existing ones are not enforced, people continue to build and live in risk prone areas. Memories of past flood events are most meaningful if they are institutionalized in changes to building codes, land use ordinances, and other local regulations affecting development, which work to prevent the recurrence of flood losses. Understanding the considerable variation in knowledge, awareness and flood preparedness among metropolitan areas in the US, may be related to how frequently a community experiences flooding-related socioeconomic loss(29).

Another potential driver of divergent approaches to flood risk is the uneven distribution of resources, in a US political economic context defined by profound and racialized disparities in income and wealth, both within and across flood-prone communities(30). Flooding events frequently serve as moments of widespread social upheaval, but their effects are patterned in ways that reflect the existing social order. Poorer and marginalized populations suffer worst, being more likely to live in already neglected environments without protective infrastructure. Across the US, residents of riverine floodplains are disproportionately the economically disadvantaged(31), who are consigned to cheaper- and more dangerous-land. Lower value properties tend to lose a greater portion of their value from flooding events than do more expensive properties(22), with deleterious long-term effects on the economic security of homeowners whose tenure may already be relatively precarious. Low-income residents and communities of color often have the hardest time recovering from flood events, as resources often flow to more affluent residents and powerful industrial interests, while the communities in need are instead exposed to downward mobility and displacement(32, 33). Residents who cannot afford to migrate after a flood may become trapped in a cycle of loss and decreasing home equity, limiting their ability to recover or relocate following future floods(17, 34). Those who do migrate-or, perhaps more accurately, are displaced-leave some US floodplains predominantly white (20, 34–36), exacerbating longer trajectories of gentrification(37). This growing area of research suggests that variations in the perceptions and community responses to floods may reflect longer histories of racialized inequality, reproduced through uneven and often discriminatory access to safe and affordable housing, as well as disaster relief.

We are confronted with the task of designing flooding risk management strategies that consider heterogeneous and unequal populations and anticipate temporal changes in risk perceptions and tolerance. Socio-hydrological (SH) models, numerical approximations of human responses to environmental stimuli, may provide a robust objective framework where complex human-flood relationships can be examined(5, 24, 38, 39). Though human-water dynamics have a history of integrated analysis in hydrology (40) the ontological aspiration in SH analysis is to capture the range of human behavior in the interaction with natural systems(41). We calibrated a current-generation SH model(42) to 50 US metropolitan areas to disaggregate and quantify potentially independent dimensions of flood risk behavior (e.g. risk tolerance vs. memory retention of past losses) and to better understand if demographics or hydrologic conditions can explain these variations. While the development and refinement of this SH model has previously relied on unified entity (community) modeling or detailed long-term records in a European context (6, 42) this work frames human-flood dynamics across a variety of US metropolitan hydrologic and social demographics. We calibrated this SH model, forced with peak annual streamflow records, to historical National Flood Insurance Program (NFIP) claims, active insurance policy records, and trends in US census derived population densities. This modeling exercise is forwarded as a means of addressing the following questions:

- Can an SH model accurately predict trends in flooding claim losses and insurance policy take up rates for US metropolitan areas from historical peak annual streamflow records?
- Which archetypal responses exist among aggregated US metropolitan area perceptions and responses to flooding?
- Do divergent flood risk behaviors of US metropolitan areas align with current hydrologic or social demographics?

2. Results

2.1 Estimation of Socio-Hydrological Parameters

Multi-Objective Generalized Sensitivity Analysis revealed that simulation of NFIP insurance claims ($RMSE_C$), active insurance policies ($RMSE_P$), and population density ($RMSE_D$) provided a sensitivity to all SH model parameter values with the exception of decay of precautionary measures (μ_p) (Fig. 1). Policy records were the most informative dataset for model parameterization, providing information on: anxiousness (α_a), activeness (α_p), preparedness (α_r), flood threshold (H), population growth rate (U), and forgetfulness (μ_a). Historical claims records and population density provided some information on the SH parameters risk taking attitude (α_d), α_a, α_p, μ_a, H, and U.

The SH model was capable of adequately predicting historical flood insurance claims, active flood policies, and population dynamics as defined by the calibration criteria ($RMSE_M < 0.025$ and $NSE_C > 0$) for a subset (50 out of 247; 20.2%) of US metropolitan areas (Fig. 2). Calibrated SH parameters demonstrated significant spatial autocorrelation in the flooding threshold, H, but not for other parameters (Fig. 2). Metropolitan areas meeting calibration thresholds had significantly more flood insurance claims per capita (λ), smaller populations (approximately less than 100,000 residents), lower maximum dam heights, smaller temporal changes in the proportion of white residents ($\Delta\%white_{2010}$) and total population (Δ Pop) than those not meeting thresholds, but were otherwise similar across all other socio-environmental demographics (Fig. 3). A comparison of SH parameterization for two contrasting metropolitan areas is presented in the SI Appendix (SI Appendix, Section S3).

We note that the parameter names previously established for this model(42) may actually represent alternative mechanisms (e.g. forgetfulness (μ_a) may more accurately describe changes in salience of flooding risks or how effectively memories of flooding risks become encoded in policy rather than literal memories).

2.2 Identification of Prototypical Flood Behaviors across US Metropolitan Areas

We identified two archetypal flood behaviors primarily by variations in three SH parameters: risk taking attitude (α_d), forgetfulness (μ_a), and population growth rate (U) (where KS-test p-value < 0.05) (Fig. 4). Of secondary importance were the flood threshold (H), activeness (α_p), and effectiveness of preparation (α_r) (where KS-test 0.05 < p-value < 0.1).

Cluster separation aligned with significant differences (p-value < 0.05) in the metropolitan area distributions of stream flashiness index (R-B) and the proportion of white residents (*%white*) (Fig. 4). Differences in poverty, home age, and partisan lean ($Lean_{538}$) between clusters were significant at the p-value < 0.1 threshold. Both clusters of metropolitan areas had similar contributing watershed areas, populations (Pop_{2018}), percentage of properties with mortgages (*%Mortgage*), density of vacancies (*Vacancy*), and rates of flood insurance claim generation (λ).

3. Discussion

3.1 Application of SH Models to US Metropolitan Areas

Our work revealed that this SH model was only a valid representation of a subset of metropolitan areas (Fig. 3). The importance of historical flooding records (λ) for determining social responses to flooding (Fig. 3) is directly interpretable: without records of substantial flooding events, the accuracy of model-simulated responses to flooding cannot be evaluated. Stronger calibration to metropolitan areas with lower populations may indicate that smaller US communities are more likely to be demographically homogenous or behave more consistently (i.e. more temporally static model parameters) with respect to floods through time than larger metropolitan areas. Further research is required to determine the appropriate scales and assumptions that may limit the applicability of SH models for understanding community flood behavior. In particular, the SH parameters were considered to be temporally invariant in both this research and in the case study(42). In reality, the composition and behavior of populations is likely constantly shifting due to changes in population density and demographics of affected people(16, 17, 25), changes in the collective memory of past floods(23), levels of experience and education(38), perceptions of risks and recovery potential(21), and the policies, publications, and economic pressures that drive population changes in flood-exposed areas(43). This possibly explains the significant variations in the change in proportion of white residents ($\Delta\%white_{2010}$) and total population (Δ Pop) (Fig. 3).

The SH model(42) includes a relatively simplistic approximation of loss resulting from over-threshold discharge events. A review of historical NFIP claims records across the US demonstrated that hazard to loss functions (i.e. the social and economic damages that results from a specific extents and durations of inundation) are heterogeneous with substantial variations by house value(22). Proper definition of hazard thresholds must extend beyond common structural considerations to include the socio-economic status of residents(44). The same event might be considered nuisance flooding to an affluent community with the means for recovery but devastating to a poorer one. While our research identified some relationships between social demographics of metropolitan areas and model performance (Fig. 3) future research may consider applying SH models in a semi-distributed manner to group regions of similar socio-economic demographics (e.g. US census tracts) and therefore possibly more similar behaviors, reflecting more analogous situations relative to privilege and disadvantage. Critical assessment of the economic and social constructs that drive the movement of people back into flood vulnerable land may yield additional insight into the dynamic forces driving housing choice in hazards areas. Examining the weight of housing choice versus societal pressures could demonstrate why collective memory events and community engagement have limited flood resilience response.

3.2 Identification of Archetypal Flood Behaviors across US Metropolitan Areas

The primary predictors of divergent SH model-derived risk behaviors were the R-B index, maximum dam height, and the proportion of white residents in metropolitan areas (Fig. 4). Clusters also aligned with home age, poverty, and political lean ($lean_{538}$) though these variables demonstrated correlation with the proportion of white residents (SI Appendix, Fig. S2). Though significant relationships were identified, the inability of the SH model to validate for a majority of metropolitan areas may limit the transferability of our conclusions to other metropolitan areas. Further, we applied the SH model to metropolitan areas as the base unit. This approach presumes homogenous populations, neglecting possible variations in perceptions and behaviors among socio-economic groups, or in how they are treated by relevant public policy. Significant relationships between demographics and behavior (Fig. 4) may indicate further work is required to disaggregate heterogeneous populations to characterize community behaviors.

Both the clustering (Fig. 4) and LASSO regression analysis (SI Appendix, Fig. S3) demonstrated the importance of the R-B index and local maximum dam height in defining community flood behaviors. LASSO specifically indicated that flashier streams correlated positively with higher flood defenses, H, and maximum dam heights were negatively correlated with risk taking attitude, α_d. This result possibly indicates that community actions or governance reflect some intuitive awareness and allowed management of local hydrologic conditions and the risks posed by streams that regularly receive surface runoff. Flashy streams, with unpredictable flow regimes and less flood control infrastructure, possibly contribute to some innate community concern for the potential consequences of floods(29). In contrast, streams that have relatively predictable flow regimes that do not deviate from expected patterns (e.g. strongly seasonal flow regimes in Mediterranean climates) and larger dams may be of less concern to communities. These variations could indicate both “green” and “technological” societies, relying on migration and investments in flood control infrastructure respectively(13). This class of SH models(5, 6, 42) incorporate the assumption that increases in community awareness and preparedness only occur in response to over-threshold flood events that cause damage (SI Appendix, Fig. S1). Despite clear variations in hazard and loss across metropolitan areas, (captured by the number of claims per capita, λ) historical claims were not predictive of H.

Conceptual models of flooding risk perceptions and insurance demand are often centered on the belief that residents have the means to purchase insurance, and vary only in how they perceive risk(10). While this paradigm possibly holds in some cities, research suggests other communities may be faced with few or no options to mitigate flooding (27) or relocate(17, 34). We observe separation between metropolitan areas with high proportions of white residents (and lower poverty) from those of racially diverse cities (with greater poverty) (Fig 4 & SI Appendix, Fig S2). The approaches to flood risk exhibited in racially diverse cities may reflect lower economic capacity among residents to participate in NFIP(45, 46) or barriers to navigating bureaucracies(35). The cluster of “risk-enduring” metropolitan areas may be cities in which residents are trapped in cycles of flooding and loss, unable to migrate from floodplains, similar to other populations(17, 34, 47), in contrast with the idea of a green society that copes with flooding through planned migration and development(13). The second cluster of risk averse metropolitan areas with a greater proportion of white residents (Fig. 4) possibly represents residents with lower barriers to participation in NFIP. For these residents, the alignment of risk averse parameter values (Fig. 4) may reflect their capacity to participate in federal programs. Furthermore, areas with more affluent residents and higher property values are better equipped to raise revenues (largely based on tax-assessed property) that will pay for the building and maintenance of expensive structural flood protection projects. Such options may be unavailable to less privileged areas, come at the expense of other public services, or require taking on large municipal debts. The positive correlation between higher flood risk defenses (H) and increasing forgetfulness (μ_a) (SI Appendix, Fig. S3) is similar to the “levee-effect” or “safe development paradox” described by others where the establishment of flood defenses can lead to a gradual (across years to decades) reduced awareness of flooding(8, 29).

3.3 Implications for US Flood Risk Mitigation

The various tools used to mitigate flood hazard and risk in the US (e.g. dam and levee construction, buyout programs, flood insurance) frequently carry hidden consequences related to shifts in community risk perceptions and behaviors (and often demographics) after implementation. Some exposure to flooding can induce individual and community actions, such as migration from floodplains that can reduce long-term vulnerability(23). Conversely, a lack of direct experience with periodic inundation in flood-prone regions, a possible outcome of dam or levee construction(6, 8), could increase the uncertainty and cognitive bias of decision makers(29) and homeowners(48), leading to non-optimal decisions concerning long-term risk management. Well-designed government assisted migration can reduce flooding risk and promote socio-economic equity(49). US state and federal (FEMA) government facilitated migration has tended to disproportionately occur in more populous and prosperous communities, where residents and local officials have the resources to navigate and withstand complex, lengthy bureaucratic processes(50, 51). These findings, coupled with a lack of decision-making transparency surrounding buyouts, has led to some criticism of these programs(16, 17).

Flood insurance programs (e.g. NFIP) may encourage resident-driven migration, and distribute losses across a broad tax base, protecting individuals from catastrophic loss; however, these dynamics frequently play out with greater complexity. Where insurance rates are less than flood losses, individuals may be encouraged to migrate into floodplains, amplifying total societal losses(52). This encouragement may come from government policies that allow the sale of subsidized housing in flood prone areas, eliciting the movement of socioeconomically disadvantaged people into these flood prone areas and thus amplifying the effects of socioeconomic status on hazard vulnerability. Other factors limiting community resilience, such as the influence of racist policies, institutions, and practices by local government may also limit the movement of vulnerable people from these hazard areas. The disproportionate rate in which disadvantaged people are encouraged to migrate into flood plains may be exacerbated through the acceleration of climate change(37).

Increases in population and development density through the monetization of hazardous land for the development of low-income housing could pose further risk for vulnerable communities who face disparate outcomes during flooding disasters. Riverine-flood influenced regions of Florida experienced increases in housing development after the establishment of NFIP, whereas coastal regions experienced decreased housing density(52). At-risk property values may decrease after publication of floodplain delineations, but housing densities remain unchanged(53). Researchers have recommended against uniform flood insurance coverage and instead proposed explicit consideration for population heterogeneity(46). Following widespread outcry about the economic effects of increasing flood insurance premiums on lower-income policyholders, FEMA has committed to introducing an “affordability framework” to the NFIP(43). Even simplistic approximations of community perceptions and responses to flood hazards, as presented in this research, could support more critical evaluations of community behaviors. Such studies are necessary to understand how socio-economic demographics and human behaviors influence exposure to risk under NFIP in US metropolitan areas. Future research should investigate the structure and calibration of SH models to improve their representation of complex human-flood interactions.

4. Methodology

4.1 Socio-Hydrological Data

We selected 247 US metropolitan core based statistical areas(54), with nearby USGS gaging stations with active records from 1950 – present (SI Appendix , Section S1). Metropolitan areas influenced by any coastal (lake or ocean) flooding events were removed from consideration through a visual map screening. We collected daily USGS streamflow records from USGS streamflow catalog (1979 – 2019)(55). Five-year population totals and annual population estimates (2010 – 2019)(54), annual NFIP flood insurance claims (1979 – 2019), and active flood policies (2009 – 2019)(56) were aggregated to metropolitan areas by census tract. The number of dams and maximum dam height were collected from the US Army Corps of Engineers National Inventory of Dams(57).

4.2 Socio-Hydrological Model Description

We applied an SH model(42) to simulate economic losses and temporal changes in population density, awareness of, and preparedness for flooding in each of the US metropolitan areas. The SH model predicts annual economic losses (USD) from a time series of annual peak riverine discharge. In response to loss events, the model simulates increases in awareness and preparedness for future floods as well as potential changes in population density. In years with no loss, community flood mitigation measures gradually decay and population density can increase. A detailed description of the SH model processes, equations, and parameters is presented in the SI Appendix (SI Appendix, Section S2). Community behaviors were defined by SH parameters related to flooding risk, vulnerability, resilience, and memory (Table 1). Initial model parameter ranges were adopted from prior research(42), and increased until calibration scores (RMSE, NSE) stabilized.

The SH model parameterization was calibrated against records of loss (NFIP claims), preparedness (active NFIP policies), and population density. The annual proportion of residents with active NFIP policies was estimated as the number of active NFIP policies divided by census estimated population (2009 – 2019). The proportion of flood losses were estimated as the annual total NFIP claims (1975 – 2018) divided by the estimated total metropolitan area property value (USD^1USD^{-1}). Metropolitan area property value was estimated as the number of properties multiplied by the average owner occupied property value(54). Annual population densities (2010-2018) were derived from the US census(54). Maximum population density was estimated as 120% of the historical maximum population(54).

Nationally, NFIP policy take-up rates rose steadily from 1978 – 2009 resulting from changes in the NFIP program(58). Since 2009, the number of active policies has steadily declined nationwide (though increases are observed in specific metropolitan areas following high riverine discharge and flooding claim generation events). We consider changes in the number of active policies within metropolitan areas from 2009 – 2019 to be reflective of attrition and uptake in community flood preparedness.

4.3 Socio-Hydrological Parameters Sensitivity and Estimation

SH model sensitivity to parameter values was evaluated with the Multi-Objective Generalized Sensitivity Analysis algorithm(59). We analyzed sensitivity for Albany, GA US with 10,000 model simulations, sampling parameters uniformly within the feasible parameter ranges presented in

Table 1. We measured sensitivity of the Root Mean Square Error (RMSE) objective function computed between observed and predicted claims ($RMSE_C$), active policies ($RMSE_P$), and population density ($RMSE_D$), as well as a measure of global sensitivity. Parameter sensitivity is discussed at α < 0.1, 0.05, and 0.01 thresholds.

Globally optimal SH model parameter vectors were estimated for all metropolitan areas with the Dynamically Dimensioned Search (DDS) algorithm(60), minimizing the function $RMSE_M = \sum(RMSE_C, RMSE_P, RMSE_D)$ across 30,000 simulations for each metropolitan area. Each calibration result was evaluated against a maximum RMSE and minimum Nash Sutcliffe Efficiency (NSE) threshold to separate meaningful calibrations from those areas that did not calibrate well. We accepted evaluations where $RMSE_M < 0.025$ and $NSE_C > 0$. The use of an NSE threshold of 0 eliminated metropolitan areas where SH estimates of historical claims was not better than the long-term average.

We tested for significant spatial-autocorrelation in calibrated SH model parameters via Moran's I. We compared SH model performance to several hydrologic and socio-economic demographic characteristics of metropolitan areas: (Richards-Baker Flashiness index [R-B], contributing watershed area [Area], number of flood claims per capita [λ], 2018 population [Pop2018], percentage of residents below the poverty line [*Poverty*], percentage of properties with a mortgage [%mortgage], median house age [*HouseAge*], the density of vacant properties [*Vacant*], the percentage of the population that is white [*%white*], partisan lean [$Lean_{538}$]), the number of NID dams, the maximum dam height, as well as changes in *%mortgage*, *Poverty*, *Vacancy*, *%white*, and total population form 2010 to 2018 (SI Appendix, Table S1). We also evaluated change in %white from 1970 – 2018(61). We estimated relationships between demographic characteristics and model performance through a two-sample Kolmogorov-Smirnov test comparing the distributions of demographics for those metropolitan areas for which the SH model produced acceptable and unacceptable calibration results. We discuss significance at the α < 0.1 and 0.05 levels.

4.4 Identification of Prototypical Flood Behaviors across US Metropolitan Areas

We identified divergent behaviors among metropolitan areas with respect to flooding hazards and risks with K-means clustering across vectors of calibrated SH parameter values for all metropolitan areas where the calibration result was accepted. The optimal number of clusters (n=2) was determined with the Calinski-Harabasz Index. We first compared the marginal distributions of each SH model parameter between the two clusters. We identified SH parameters (Table 1) to which the clustering algorithm was sensitive with a 2-sample Kolmogorov-Smirnov test. Significance is assessed at the α < 0.1 and α < 0.05 levels.

Next, we compared the empirical distributions of hydrologic and social demographic characteristics (SI Appendix, Table S1) between metropolitan areas in each of the two clusters to determine if social or hydrologic conditions drive community behavior with respect to flooding. Significance is determined with a 2-sample Kolmogorov-Smirnov test (significance is assessed at the α < 0.1 and α < 0.05 levels).

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6. References

1. World Resources Institute, RELEASE: New Data Shows Millions of People, Trillions in Property at Risk from Flooding — But Infrastructure Investments Now Can Significantly Lower Flood Risk. *World Resources Institute* (2020) (August 8, 2020).

2. A. B. Smith, NOAA National Centers For Environmental Information, U.S. Billion-dollar Weather and Climate Disasters, 1980 - present (NCEI Accession 0209268) (2020) https:/doi.org/10.25921/STKW-7W73 (August 8, 2020).

3. W. Kron, Flood Risk = Hazard • Values • Vulnerability. *Water International* **30**, 58–68 (2005).

4. G. A. Tobin, The Levee Love Affair: A Stormy Relationship? *JAWRA Journal of the American Water Resources Association* **31**, 359–367 (1995).

5. M. H. Barendrecht, A. Viglione, G. Blöschl, A dynamic framework for flood risk. *Water Security* **1**, 3–11 (2017).

6. G. D. Baldassarre, *et al.*, Socio-hydrology: conceptualising human-flood interactions. *Hydrology and Earth System Sciences* **17**, 3295–3303 (2013).

7. T. Haer, W. J. W. Botzen, J. C. J. H. Aerts, Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modelling approach. *Environ. Res. Lett.* **14**, 044022 (2019).

8. T. Haer, T. G. Husby, W. J. W. Botzen, J. C. J. H. Aerts, The safe development paradox: An agent-based model for flood risk under climate change in the European Union. *Global Environmental Change* **60**, 102009 (2020).

9. A. Plough, *et al.*, Building Community Disaster Resilience: Perspectives From a Large Urban County Department of Public Health. *Am J Public Health* **103**, 1190–1197 (2013).

10. P. J. Robinson, W. J. W. Botzen, Determinants of Probability Neglect and Risk Attitudes for Disaster Risk: An Online Experimental Study of Flood Insurance Demand among Homeowners. *Risk Analysis* **39**, 2514–2527 (2019).

11. A. Serra-Llobet, E. Conrad, K. Schaefer, Governing for Integrated Water and Flood Risk Management: Comparing Top-Down and Bottom-Up Approaches in Spain and California. *Water* **8**, 445 (2016).

12. K. Tierney, *The Social Roots of Risk: Producing Disasters, Promoting Resilience* (Stanford University Press, 2014).

13. G. D. Baldassarre, *et al.*, Debates—Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes. *Water Resources Research* **51**, 4770–4781 (2015).

14. J. Mård, G. D. Baldassarre, M. Mazzoleni, Nighttime light data reveal how flood protection shapes human proximity to rivers. *Science Advances* **4**, eaar5779 (2018).

15. K. M. O'Neill, *Rivers by Design: State Power and the Origins of U.S. Flood Control* (Duke University Press, 2006).

16. K. J. Mach, *et al.*, Managed retreat through voluntary buyouts of flood-prone properties. *Science Advances* **5**, eaax8995 (2019).

17. A. R. Siders, Managed Retreat in the United States. *One Earth* **1**, 216–225 (2019).

18. L. Koslov, The Case for Retreat. *Public Culture* **28**, 359–387 (2016).

19. S. Birkholz, M. Muro, P. Jeffrey, H. M. Smith, Rethinking the relationship between flood risk perception and flood management. *Science of The Total Environment* **478**, 12–20 (2014).

20. J. Knighton, *et al.*, Predicting flood insurance claims with hydrologic and socioeconomic demographics via machine learning: Exploring the roles of topography, minority populations, and political dissimilarity. *Journal of Environmental Management* **272**, 111051 (2020).

21. D. R. Petrolia, C. E. Landry, K. H. Coble, Risk Preferences, Risk Perceptions, and Flood Insurance. *Land Economics* **89**, 227–245 (2013).

22. O. E. J. Wing, N. Pinter, P. D. Bates, C. Kousky, New insights into US flood vulnerability revealed from flood insurance big data. *Nature Communications* **11**, 1444 (2020).

23. V. Fanta, M. Šálek, P. Sklenicka, How long do floods throughout the millennium remain in the collective memory? *Nature Communications* **10**, 1105 (2019).

24. D. H. de Vries, Temporal vulnerability in hazardscapes: Flood memory-networks and referentiality along the North Carolina Neuse River (USA). *Global Environmental Change* **21**, 154–164 (2011).

25. R. A. Collenteur, H. de Moel, B. Jongman, G. Di Baldassarre, The failed-levee effect: Do societies learn from flood disasters? *Nat Hazards* **76**, 373–388 (2015).

26. E. Zavar, R. R. Hagelman III, Land use change on U.S. floodplain buyout sites, 1990-2000. *Disaster Prevention and Management* **25**, 360–374 (2016).

27. R. Elliott, 'Scarier than another storm': values at risk in the mapping and insuring of US floodplains. *The British Journal of Sociology* **70**, 1067–1090 (2019).

28. A. Atreya, S. Ferreira, E. Michel-Kerjan, What drives households to buy flood insurance? New evidence from Georgia. *Ecological Economics* **117**, 153–161 (2015).

29. B. Merz, S. Vorogushyn, U. Lall, A. Viglione, G. Blöschl, Charting unknown waters—On the role of surprise in flood risk assessment and management. *Water Resources Research* **51**, 6399–6416 (2015).

30. J. E. Givens, X. Huang, A. K. Jorgenson, Ecologically unequal exchange: A theory of global environmental injustice. *Sociology Compass* **13**, e12693 (2019).

31. Y. Qiang, Disparities of population exposed to flood hazards in the United States. *Journal of Environmental Management* **232**, 295–304 (2019).

32. K. F. Gotham, M. Greenberg, *Crisis Cities: Disaster and Redevelopment in New York and New Orleans* (Oxford University Press, 2014).

33. W. R. Freudenburg, R. B. Gramling, S. Laska, K. Erikson, *Catastrophe in the Making: The Engineering of Katrina and the Disasters of Tomorrow* (Island Press, 2009).

34. J. Grames, A. Prskawetz, D. Grass, A. Viglione, G. Blöschl, Modeling the interaction between flooding events and economic growth. *Ecological Economics* **129**, 193–209 (2016).

35. J. R. Elliott, Natural Hazards and Residential Mobility: General Patterns and Racially Unequal Outcomes in the United States. *Soc Forces* **93**, 1723–1747 (2015).

36. S. L. Cutter, C. T. Emrich, M. Gall, R. Reeves, Flash Flood Risk and the Paradox of Urban Development. *Natural Hazards Review* **19**, 05017005 (2018).

37. J. M. Keenan, T. Hill, A. Gumber, Climate gentrification: from theory to empiricism in Miami-Dade County, Florida. *Environ. Res. Lett.* **13**, 054001 (2018).

38. T. Haer, W. J. W. Botzen, H. de Moel, J. C. J. H. Aerts, Integrating Household Risk Mitigation Behavior in Flood Risk Analysis: An Agent-Based Model Approach. *Risk Analysis* **37**, 1977–1992 (2017).

39. K. E. Kaiser, A. N. Flores, V. Hillis, Identifying emergent agent types and effective practices for portability, scalability, and intercomparison in water resource agent-based models. *Environmental Modelling & Software* **127**, 104671 (2020).

40. R. M. Vogel, *et al.*, Hydrology: The interdisciplinary science of water. *Water Resources Research* **51**, 4409–4430 (2015).

41. A. Wesselink, M. Kooy, J. Warner, Socio-hydrology and hydrosocial analysis: toward dialogues across disciplines. *WIREs Water* **4**, e1196 (2017).

42. M. H. Barendrecht, *et al.*, The Value of Empirical Data for Estimating the Parameters of a Sociohydrological Flood Risk Model. *Water Resources Research* **55**, 1312–1336 (2019).

43. R. Elliott, Who Pays for the Next Wave? The American Welfare State and Responsibility for Flood Risk. *Politics & Society* **45**, 415–440 (2017).

44. L. E. McPhillips, *et al.*, Defining Extreme Events: A Cross-Disciplinary Review. *Earth's Future* **6**, 441–455 (2018).

45. L. Dixon, *et al.*, The Cost and Affordability of Flood Insurance in New York City: Economic Impacts of Rising Premiums and Policy Options for One- to Four-Family Homes (2017) (August 7, 2020).

46. E. E. Koks, B. Jongman, T. G. Husby, W. J. W. Botzen, Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. *Environmental Science & Policy* **47**, 42–52 (2015).

47. R. L. Hale, C. G. Flint, D. Jackson-Smith, J. Endter-Wada, Social Dimensions of Urban Flood Experience, Exposure, and Concern. *JAWRA Journal of the American Water Resources Association* **54**, 1137–1150 (2018).

48. J. Gallagher, Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States. *American Economic Journal: Applied Economics* **6**, 206–233 (2014).

49. H. Randell, Structure and agency in development-induced forced migration: the case of Brazil's Belo Monte Dam. *Popul Environ* **37**, 265–287 (2016).

50. K. Loughran, J. R. Elliott, Residential buyouts as environmental mobility: examining where homeowners move to illuminate social inequities in climate adaptation. *Popul Environ* **41**, 52–70 (2019).

51. A. Weber, R. Moore, Going Under: Long Wait Times for Post-Flood Buyouts Leave Homeowners Underwater | NRDC (2019) (August 7, 2020).

52. M. J. Browne, C. A. Dehring, D. L. Eckles, W. D. Lastrapes, Does National Flood Insurance Program Participation Induce Housing Development? *Journal of Risk and Insurance* **86**, 835–859 (2019).

53. A. Indaco, F. Ortega, S. Taşpınar, The Effects of Flood Insurance on Housing Markets. *Cityscape* **21**, 129–156 (2019).

54. US Census Bureau, Metropolitan and Micropolitan Statistical Areas Totals: 2010-2019. *The United States Census Bureau* (August 7, 2020).

55. US Geological Survey, Surface-Water Historical Instantaneous Data for the Nation: Build Time Series (August 7, 2020).

56. US FEMA, OpenFEMA Data Sets | FEMA.gov (August 7, 2020).

57. USACE, National Inventory of Dams (NID) - Home. *National Inventory of Dams* (2020) (December 2, 2020).

58. C. Kousky, Financing Flood Losses: A Discussion of the National Flood Insurance Program. *Risk Management and Insurance Review* **21**, 11–32 (2018).

59. L. A. Bastidas, H. V. Gupta, S. Sorooshian, W. J. Shuttleworth, Z. L. Yang, Sensitivity analysis of a land surface scheme using multicriteria methods. *Journal of Geophysical Research: Atmospheres* **104**, 19481–19490 (1999).

60. B. A. Tolson, C. A. Shoemaker, Dynamically dimensioned search algorithm for computationally efficient watershed model calibration. *Water Resources Research* **43** (2007).

61. S. Manson, J. Schroeder, D. Van Riper, T. Kugler, S. Ruggles, IPUMS NHGIS. *IPUMS NIPUMS National Historical Geographic Information System: Version 15.0 [dataset].HGIS* (December 3, 2020).

Figures and Tables

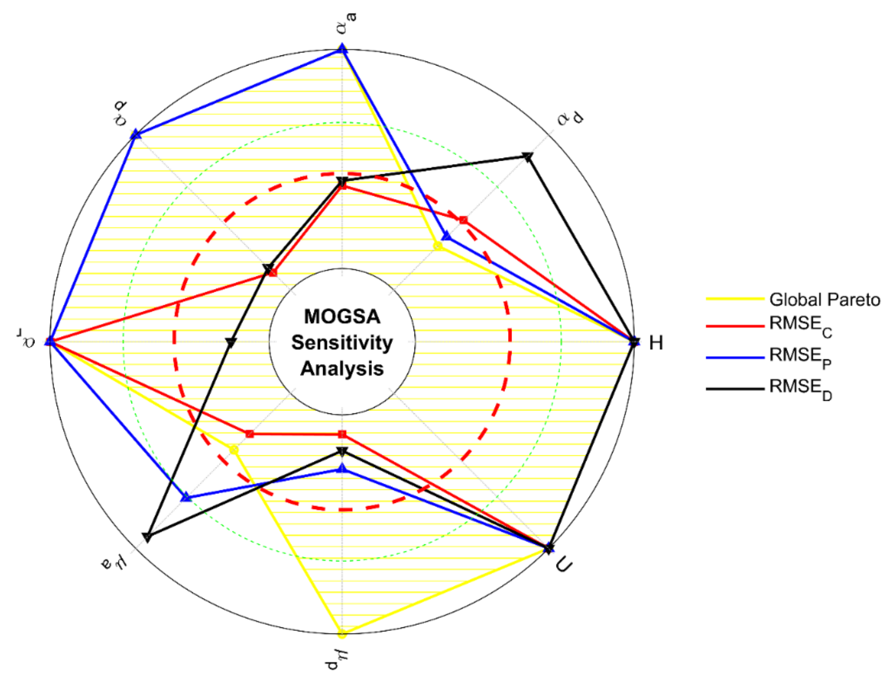

Fig. 1. Sensitivity of Root Mean Square Error (RMSE) computed from claims (C, red), policies (P, blue), population density (D, black), and global sensitivity (yellow). Socio-hydrologic parameter significance is presented at the α = 0.1 (red ring), 0.05 (green ring), 0.01 (black ring) levels. Model parameters include: discharge threshold for flooding losses (H), risk taking attitude (α_d), anxiousness (α_a), activeness (α_p), effectiveness of preparation (α_r), forgetfulness (μ_a), decay of precautionary measures (μ_p), and ambient population growth rate (U).

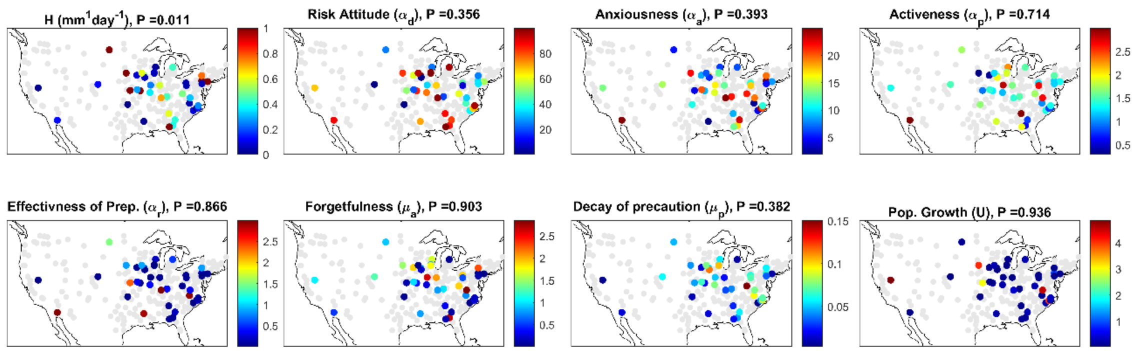

Fig. 2. Calibrated SH model parameter values (colors). Gray dots indicate metropolitan areas that did not meet calibration thresholds. P-values are the significance of Moran's I test for spatial autocorrelation.

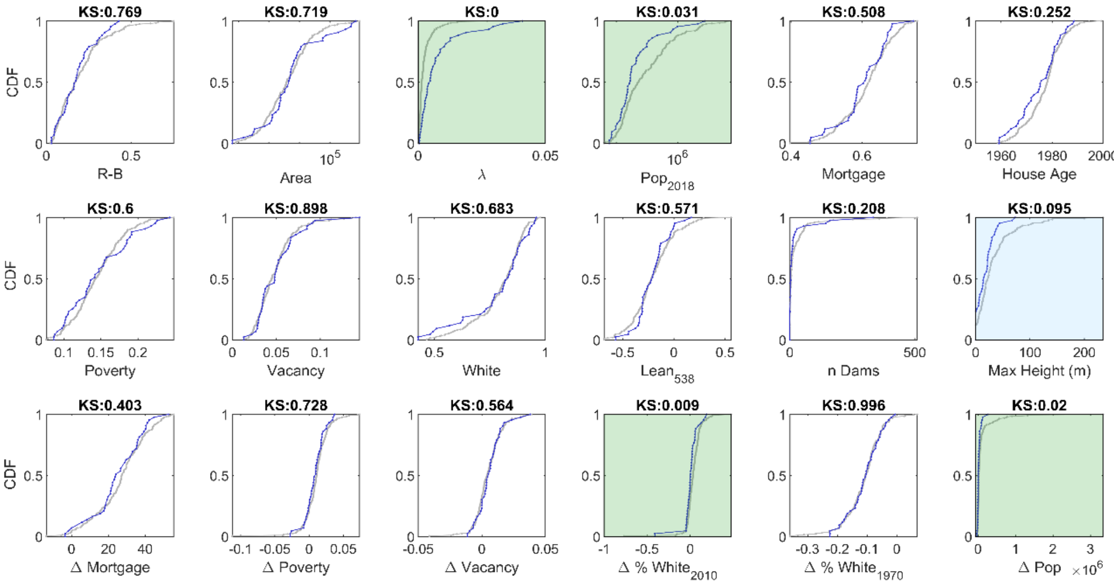

Fig. 3. Socio-hydrologic demographics for metropolitan areas meeting calibration thresholds (blue) and metropolitan areas not meeting calibration thresholds (gray). KS indicates the 2-sample KS-test p-value. Green shading indicates significance at α < 0.05. Blue shading indicates significance at α < 0.1.

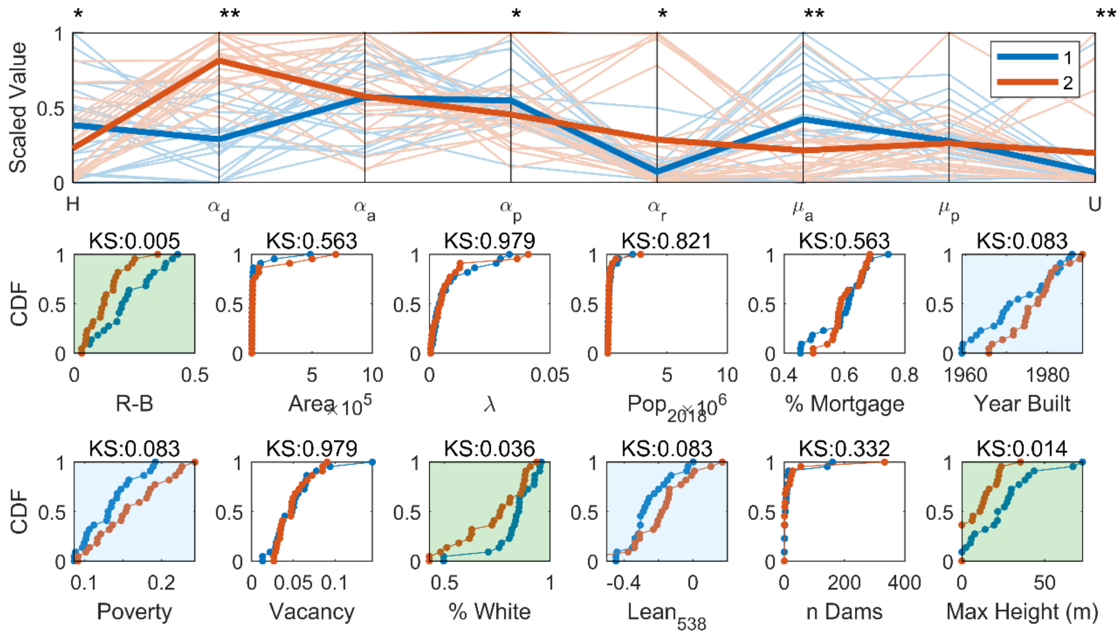

Fig. 4. Parallel axis plot showing k-means cluster analysis of SH model parameters (top). Dark lines indicate prototypical SH clusters, light lines indicate calibrated model parameter sets for individual cities within each cluster. Significant parameter separation at the α < 0.05 and 0.1 thresholds are indicated by ** and * respectively. Empirical distributions of socio-hydrologic demographics for each of the identified clusters (bottom). KS indicates 2-sample KS-test p-value. Green shading indicates significance at α < 0.05. Blue shading indicates significance at α < 0.1.

Table 1. Socio-hydrological model parameters(42) and feasible ranges used for metropolitan area calibration. H_{MAX} indicates the feasible upper limit of peak discharge. n_h and n_m represent the number of properties within the study area and the number of precautionary measures, respectively. The model time step is *t*.

Parameter	Description	Feasible Range
H [mm]	discharge threshold for flooding losses	(0, H_{MAX})
α_d [(1/(n_h/n_h))]	risk taking attitude	(0.001,100)
α_a (1/(USD/USD))	anxiousness	(0.001,25)
α_p [((n_m/n_m)/(n_h/n_h))]	activeness	(0.001,3)
α_r [(1/(n_m/n_m))]	effectiveness of preparation	(0.001,3)
β_R [((USD/m^2)/(USD/m^2))]	Over-threshold discharge to loss ratio	1
μ_a [t^{-1}]	forgetfulness	(0.001,3)
μ_p [t^{-1}]	decay of precautionary measures	(0.001,3)
U [t^{-1}]	ambient population growth rate	(0.001,5)