

Flood risk behaviors of United States riverine metropolitan areas are driven by local hydrology and shaped by race

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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 US 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 SH 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.

sociohydrology | flood risk | insurance | hydrology | hydrologic modeling

Global annual riverine flooding losses are projected to rise from \$45 billion USD in 2019 to \$335 billion USD by 2050 (1). Annual average flooding losses across the United States 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 United States, 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 United States 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

Significance

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 United States.

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of hydrologic risks (23). Experience with floods may increase homeowners' 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. The considerable variation in knowledge, awareness, and flood preparedness among metropolitan areas in the United States 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 United States, 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. Sociohydrologic (SH) models, numerical approximations of human responses to environmental stimuli, may provide a robust objective framework through which 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 versus 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?

Results

Estimation of SH Parameters. Multiobjective generalized sensitivity analysis revealed that simulation of NFIP insurance claims (root mean square error $[RMSE]_C$), 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 ,

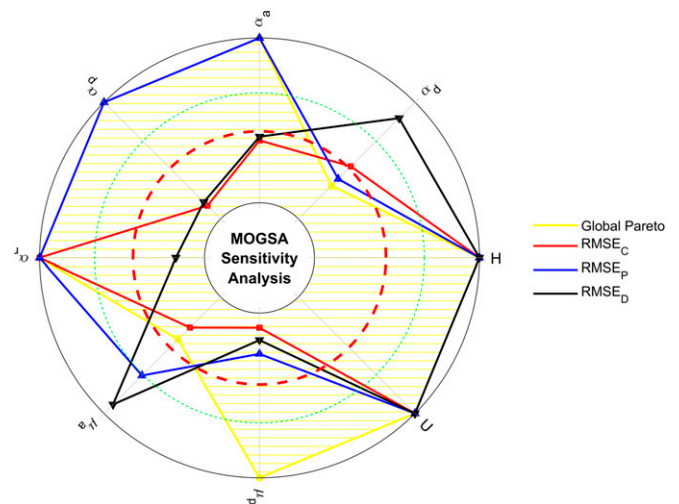


Fig. 1. Multi-Objective Generalized Sensitivity Analysis (MOGSA) of RMSE computed from claims (C, red), policies (P, blue), population density (D, black), and global sensitivity (yellow). SH parameter significance is presented at the $\alpha = 0.1$ (red ring), 0.05 (green ring), and 0.01 (black ring) levels.

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, and smaller temporal changes in the proportion of White residents ($\Delta\% \text{White}_{2010}$) and total population (ΔPop) than those not meeting thresholds but were otherwise similar across all other socioenvironmental demographics (Fig. 3). A comparison of SH parameterization for two contrasting metropolitan areas is presented in *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).

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 Kolmogorov–Smirnov (KS) test $P < 0.05$) (Fig. 4). Of secondary importance were the flood threshold (H), activeness (α_p), and effectiveness of preparation (α_r) (where KS-test $0.05 < P < 0.1$).

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

Discussion

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 ($\Delta\% \text{White}_{2010}$) and total population (ΔPop) (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 United States 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 socioeconomic 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 semidistributed manner to group regions of similar socioeconomic 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.

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. Furthermore, we applied the SH model to metropolitan areas as the base unit. This approach presumes homogenous

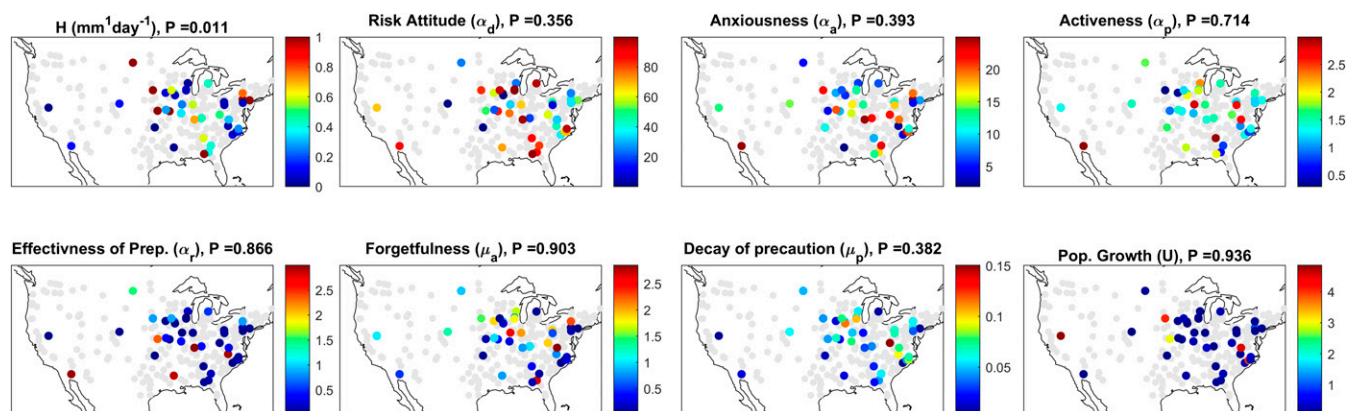


Fig. 2. Calibrated SH model parameter values (colors). Gray dots indicate metropolitan areas that did not meet calibration thresholds.

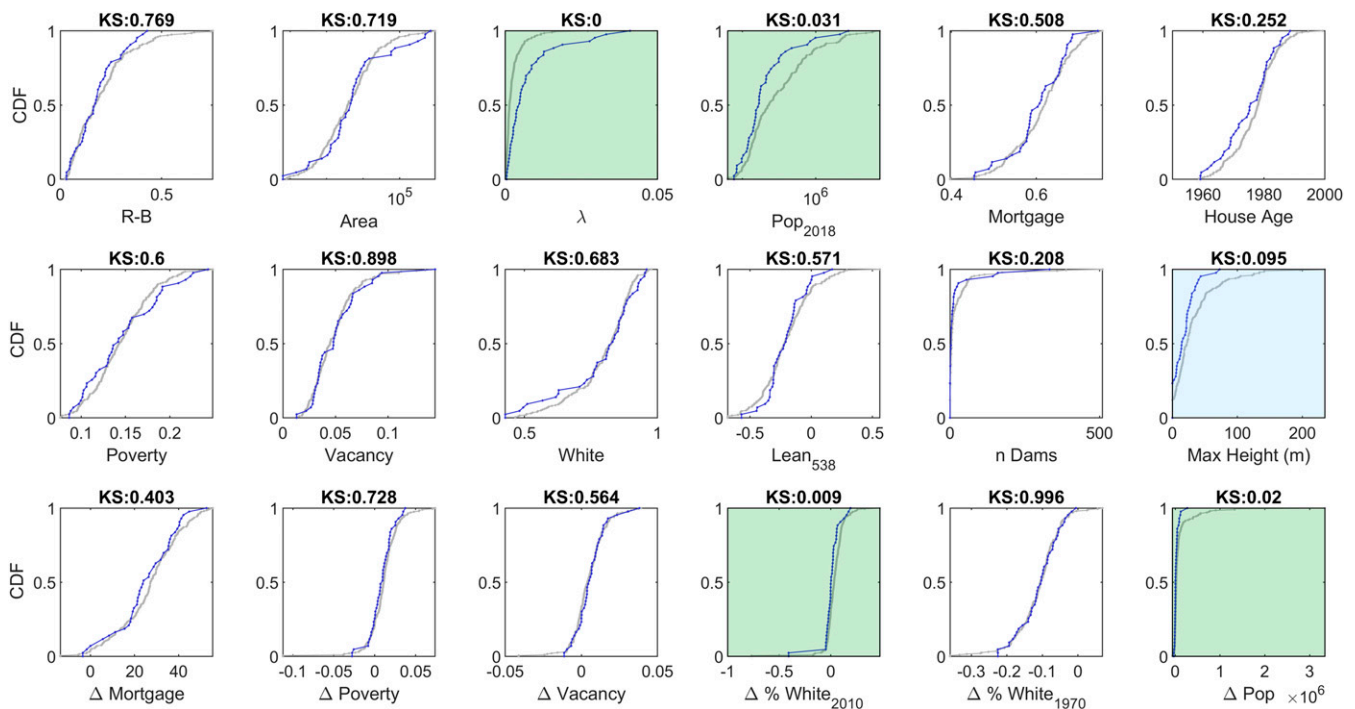


Fig. 3. SH demographics for metropolitan areas meeting calibration thresholds (blue) and metropolitan areas not meeting calibration thresholds (gray). KS indicates the two-sample KS-test P value, where green shading indicates significant separation.

populations, neglecting possible variations in perceptions and behaviors among socioeconomic 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 least absolute shrinkage and selection operator (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) incorporates 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 to 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 and 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).

Implications for US Flood Risk Mitigation. The various tools used to mitigate flood hazard and risk in the United States (e.g., dam and levee construction, buyout programs, and 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

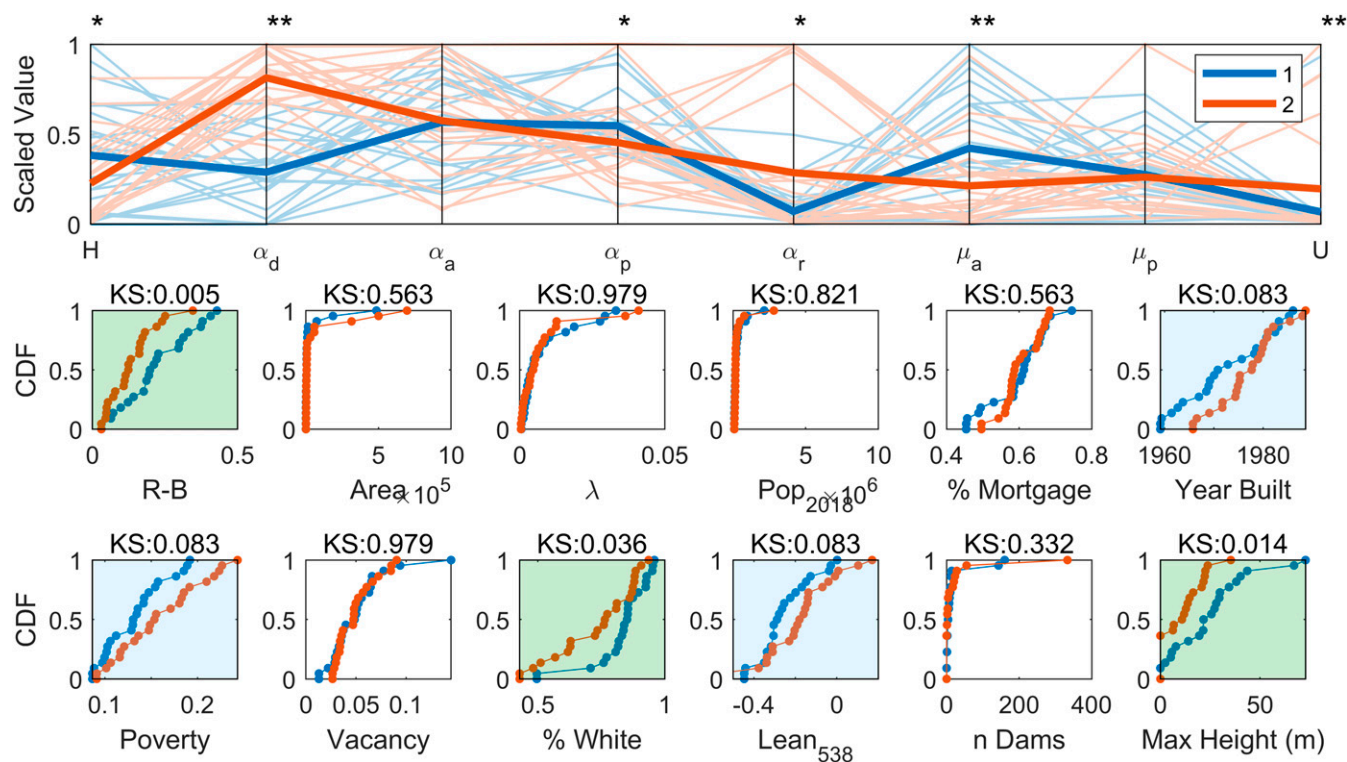


Fig. 4. Parallel axis plot showing K-means cluster analysis of SH model parameters (Top). Dark lines indicate prototypical SH clusters, light lines indicate calibrated model parameter sets for individual cities within each cluster. Significant parameter separation at the $\alpha < 0.05$ and 0.1 thresholds are indicated by ** and *, respectively. (Bottom) Empirical distributions of SH demographics for each of the identified clusters. KS indicates two-sample KS-test P value. Green shading indicates sensitivity at $\alpha < 0.05$. Blue shading indicates sensitivity at $\alpha < 0.1$.

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 socioeconomic equity (49). US state and Federal Emergency Management Agency (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 socioeconomic 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.

Methodology

SH Data. We selected 247 US metropolitan core-based statistical areas (54), with nearby US Geological Survey (USGS) gaging stations with active records from 1950 to 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 (1950 to 2019) (55). Five-year population totals and annual population estimates (2010 to 2019) (54), annual NFIP flood insurance claims (1979 to 2019), and active flood policies (2009 to 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).

Table 1. SH model parameters (42) and feasible ranges used for metropolitan area calibration

Parameter	Description	Feasible range
H [mm]	Discharge threshold for flooding losses	0, H_{MAX}
$\alpha_d [(1/(n_h/n_h))]$	Risk-taking attitude	0.001,100
$\alpha_a (1/(USD/USD))$	Anxiousness	0.001,25
$\alpha_p [((n_m/n_m)/(n_h/n_h))]$	Activeness	0.001,3
$\alpha_r [(1/(n_m/n_m))]$	Effectiveness of preparation	0.001,3
$\beta_R [((USD/m^2)/(USD/m^2))]$	Over-threshold discharge to loss ratio	1
$\mu_a [t^{-1}]$	Forgetfulness	0.001,3
$\mu_p [t^{-1}]$	Decay of precautionary measures	0.001,3
U [t^{-1}]	Ambient population growth rate	0.001,5

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 .

SH Model Description. We applied an SH model (42) to simulate economic losses and temporal changes in population density and awareness of and preparedness for flooding in each of the US metropolitan areas. The SH model predicts annual economic losses (in 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, 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, Nash Sutcliffe efficiency [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 to 2019). The proportion of flood losses were estimated as the annual total NFIP claims (1975 to 2018) divided by the estimated total metropolitan area property value ($USD^1 USD^{-1}$). Metropolitan area property value was estimated as the number of properties multiplied by the average owner-occupied property value (54). Annual population densities (2010 to 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 to 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 to 2019 to be reflective of attrition and uptake in community flood preparedness.

SH Parameter Sensitivity and Estimation. SH model sensitivity to parameter values was evaluated with the multiobjective generalized sensitivity analysis algorithm (59). We analyzed sensitivity for Albany, Georgia, with 10,000 model simulations, sampling parameters uniformly within the feasible parameter ranges presented in Table 1. We measured sensitivity of the 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 $\alpha < 0.1$, 0.05, and 0.01 thresholds.

Globally optimal SH model parameter vectors were estimated for all metropolitan areas with the dynamically dimensioned search 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 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 socioeconomic demographic characteristics of metropolitan areas (R-B index, 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 [Lean₅₃₈]), the National Inventory of Dams number of dams, the maximum dam height, and changes in %mortgage, Poverty, Vacancy, %White, and total population from 2010 to 2018 (*SI Appendix, Table S1*). We also evaluated change in %White from 1970 to 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 $\alpha < 0.1$ and 0.05 levels.

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 two-sample Kolmogorov–Smirnov test. Significance is assessed at the $\alpha < 0.1$ and $\alpha < 0.05$ 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 two-sample Kolmogorov–Smirnov test (significance is assessed at the $\alpha < 0.1$ and $\alpha < 0.05$ levels).

Data Availability. All study data are included in the article and/or *SI Appendix*.

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