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From opinion to action: Impact of social networks and information policy on private adaptation to floods

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ABSTRACT

Despite efforts to mitigate climate change, adaptation becomes critical. Among climate-induced hazards, flooding is the most costly and widespread, calling for adaptation across scales: from government-led to household-led adaptation. Private adaptation measures, if taken, reduce damages and speed up recovery. Empirical evidence suggests that among socio-behavioral factors, social norms and peer influence are crucial for households' decisions to adapt. Yet, the role social networks play in household-level adaptation has not been studied systematically, even less so the interplay between private household adaptation and public information policies in the presence of social influences, the exchange of opinions and information within a social network that impacts individuals' decisions. To improve the understanding of the impact of social influence on private household adaptation uptake, we build an empirically informed agent-based model of household behavior. We leverage household survey data collected in Harris County (Texas, USA) together with information on flood hazard scenarios to study the impact of private adaptation diffusion on flood damages under different social influence scenarios. Furthermore, we use the model to test how different information policy design choices—such as targeting specific households or all, and communicating different aspects of flood adaptation (e.g., flood damage, costs, or effectiveness of measures) –influence private adaptation diffusion and impact regional residual flood damage. We find that regardless of the structure of the social network, social influence triggers higher adaptation uptake by households, resulting in a 5–10% extra reduction in regional residual flood damage. Notably, the effect of social norms depends on the type of information exchanged within networks, where the opinion exchange on the effectiveness of measures and potential damages results in more private adaptation compared to the discussion on perceived costs of adaptation measures or the worry about flooding. Moreover, while information campaigns influence individual perceptions that facilitate household-led adaptation, the provision of information solely on expected damages is not as effective in steering public opinion and, thereby household adaptation, as its combination with information on coping measures that enable action. Our results demonstrate that social influence and information policy can shape the success of private action and highlight the importance of understanding the interaction among scales in climate change adaptation.

1. Introduction

Adverse climate change impacts are increasingly experienced and expected to grow in intensity and frequency (IPCC, 2022). Floods – including pluvial, fluvial, and coastal flooding – are the costliest and most widespread hazards, with coastal storms and floods constituting 72% of all hazards worldwide and accounting for 69% of all global damages (CRED and UNDRR, 2020). Effective adaptation across scales is vital (Adger et al., 2005; Berrang-Ford et al., 2021). In addition to public, government-led climate change adaptation (CCA), private, household-led adaptations are becoming increasingly important for managing risks of climate-driven hazards. While public adaptation typically reduces the probability of occurrence of a hazard event, private CCA aims to decrease physical vulnerability and sometimes exposure (if

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people decide to relocate), reducing direct damages to households should a hazard event occur. Private flood adaptation measures such as wet-proofing (sealing), gathering information about flood risk, or moving assets to higher floors (Koerth et al., 2017) could reduce flood damage by 25–50% (Sairam et al., 2019), or even up to 85% (Kreibich et al., 2015), if taken.

Even though private CCA is often cost-effective, households tend to ignore or postpone it or maladapt by taking ineffective actions. Financial, awareness, cultural, and other adaptation constraints prevent households from taking CCA action (Thomas et al., 2021). Household surveys provide rich evidence on factors motivating households' CCA decisions, consistently stressing that behavioral and social factors are more decisive for household CCA uptake than rational assessments of probabilities and damages (e.g., Bubeck et al., 2012a, 2012b; Duijndam et al., 2023; van Valkengoed and Steg, 2019; Noll et al., 2022). Since private adaptation decisions are largely based on subjective perceptions (Grothmann and Reusswig, 2006), the literature highlights the special role of social networks, social influence and norms on people's CCA (Wilson et al., 2020). In the context of decisions under risk and CCA, social influence manifests mainly via dynamics of subjective opinions about risks and adaptation options, as well as via evolving social norms as individuals change their behavior, leading to a shift in norms (Bubeck et al., 2018). In this context, we define social influence as the opinion exchange within a certain social network structure, also known as opinion dynamics, that influence individuals' decision-making.

When social influence attenuates the individual intentions to adapt, it is referred to as the "soft" limits of adaptation (Thomas et al., 2021) and could lead to an adaptation deficit (Gawith et al., 2020). Evolving soft limits to adaptation lead to changes in households' behavior substantial enough to alter regional residual damages (Taberna et al., 2023). Besides social influence, information policies could nudge individuals towards desired behavior, like promoting private CCA (Benartzi et al., 2017). Yet, the interplay between information campaigns and social influence remains unexplored, despite being crucial in the context of private CCA. Therefore, it is important to understand the role of social influence and how it facilitates or hinders CCA policy and eventual damage reduction.

Among methods to explore the role of private CCA in risk assessments, agent-based models (ABMs) become increasingly popular (Taberna et al., 2020). Since rules about individual actions and interactions of many boundedly-rational diverse agents can be explicitly coded in ABMs, such models are especially well suited to study the effects of information policies and social influence (Aerts, 2020; Filatova et al., 2013). The former is commonly modeled as a provision of facts to households; the latter typically includes opinion dynamics that update both individual beliefs and social norms. Some studies of social influence have meticulously mapped relationships (e.g., Cunningham et al., 2016), while others define the social network based on simple spatial proximity (e.g., neighbors in Haer et al., 2016). Yet, the structural testing of the effects of social influence in the context of CCA is missing. Because social networks are not uniform, how this influence spreads might matter for the outcomes of interest like CCA diffusion and residual damage reduction. Furthermore, how the evolution of subjective opinions via social networks affects individual decisions is also mediated by the information on objective risks or CCA options people might be receiving via information policy campaigns.

Social influence plays an important role in private flood adaptation, particularly because the decision to adapt is strongly driven by perceptions (e.g., Grothmann and Reusswig, 2006; Noll et al., 2022; van Valkengoed and Steg, 2019). ABMs can combine theoretical and empirical aspects of networks to explore human interactions (Will et al., 2020). While many flood-related ABMs employ some form of social influence (Taberna et al., 2020), the choice of information to exchange as well as the structure of a social network is often ad hoc and has not been tested systematically. Outside CCA and hazard reduction studies, opinion dynamics and information exchange are frequently examined with ABMs (Flache et al., 2017; Will et al., 2020). While there have been many advancements on this front, previous researchers have often focused on issues like polarization, hardly linking shifting opinions to subsequent changes in behavior. In this work, we combine theoretical insights on social influence with empirical observations from surveys to model households' private CCA decisions, to observe the impact of opinion diffusion across various social networks on households' adaptation uptake, and the cumulative impacts of these dynamics on the aggregated regional damages.

To address the gaps in the literature, we explore the speed and extent of private CCA diffusion and the corresponding influence on regional residual flood damage while systematically varying flood scenarios, social network configurations, type of information exchanged and information policies. To this end, we aim to shed light on the following research questions:

1. How do social dynamics influence adaptation diffusion among households?
2. How do these dynamics affect differences in adaptation uptake and the distribution of benefits between low versus high income households?
3. To what extent do various information policies (i.e. type of information communicated) impact private adaptation diffusion and the overall regional damages?

To address these research questions, we develop an ABM with solid theoretical and empirical behavioral foundations for private CCA behavior. Households' behavior relies on Protection Motivation Theory (PMT) (Grothmann and Reusswig, 2006) and is grounded in microdata from surveys on flood adaptation behavior in Harris County, Texas, USA (Filatova et al., 2022). We then systematically design computational experiments to vary hazard occurrence using three flood inundation scenarios as inputs in our ABM. Furthermore, instead of assuming one ad hoc social network, we expand the experiment design to vary social influence dynamics by testing three common network structures, which serve as channels for households' opinion dynamics and for aligning with evolving social norms. Lastly, to study the effect of various information policy designs, we vary the type of information being communicated (i.e. the scope – about risk or coping appraisal), the intensity of information about the hazard severity (i.e. a regular flood vs. extreme events which become more common with climate change), and the recipients of information (i.e. selectivity - communicating to floodplain residents vs. to all).

The paper proceeds as follows. First, the Methods section presents our ABM of private CCA behavior, social influence, and information policies. To address the research questions, we explain the design of computational experiments and present the key Results. We conclude with discussing the role of social influence and information policies for private CCA diffusion and the resulting residual damages, including their distribution between households.

2. Methods

2.1. Agent-based model of private adaptation to floods, social influence and information policy

To study the effect of social influence on households' CCA behavior, we employ agent-based computational modeling. ABMs allow us to model agents, in this case, households, their individual choices, as well as interaction with others, and the patterns that emerge from it (Macal, 2016; Will et al., 2020). Our model operates on three levels (Fig. 1): the private CCA behavior of households (micro level), the social influence among them (meso level), and the information policies by governments that intend to inform households about risks (macro level). As a case study, we choose Harris County, Texas, which encompasses the metropolitan area of Houston and is the third largest county by population in

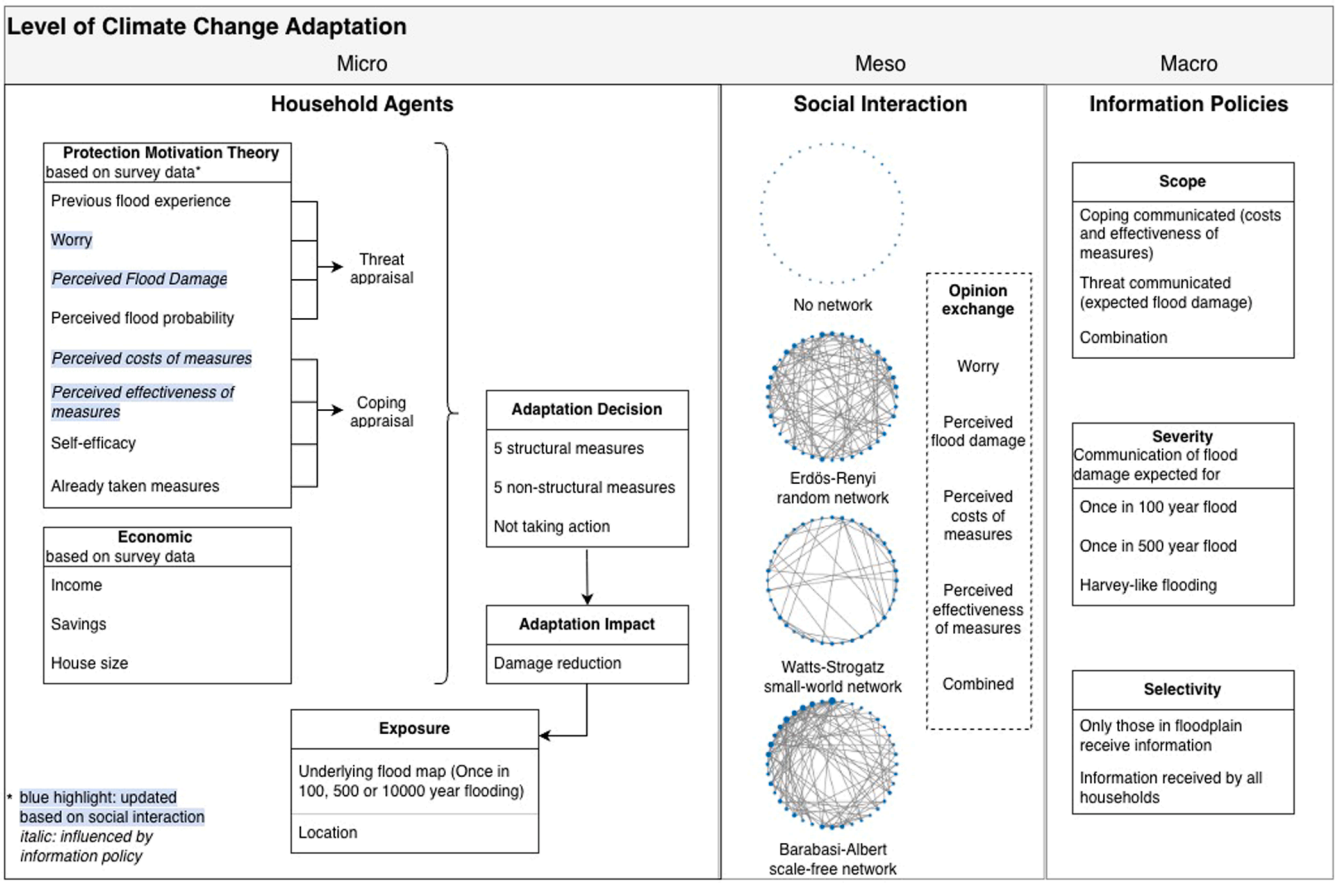

Fig. 1. Different levels of climate change adaptation considered in this work and coded in our agent-based model. On the Micro-level (left) are the households who take decisions about private adaptation measures based on Protection Motivation Theory and own economic status. Overlayed with individual exposure, this individual behavior results in damage reduction for each household. On the Meso-level (middle), households interact with each other through different forms of social networks and exchange opinions about different types of information. At the Macro-level (right), different information policies varying in Scope, Severity and Selectivity, influence individual adaptation behavior.

the USA. This highly urbanized area is subject to frequent flooding from tropical cyclones and heavy rainfall. In 2017, Hurricane Harvey made landfall in south Texas causing an estimated $125 billion USD in damage – much of which occurred in Harris County - making it the second costliest storm in the U.S. on record (NCEI, 2022).

2.1.1. *Private household adaptation behavior (Micro Level)*

We run the ABM with a population of 1000 heterogeneous households.[1] The household agents are initialized using survey data gathered in Harris County with a focus on better understanding the adaptation decision process of households (Filatova et al., 2022). Here, we employ the results from the first wave of the survey conducted in April 2020 (Noll et al., 2022; Noll et al., 2022), containing answers from 849 Harris County households. We relied on online surveys administered via YouGov,[2] with respondents sampled across three US states from the representative panels that match national statistics. The Supplementary Material contains more information on how the survey data is used in the model. The household agents can choose between ten CCA measures, encompassing the five common structural and five non-structural measures (details in Appendix A). By taking adaptation measures, household agents can reduce the potential flood damage, with various measures leading to different damage reductions (Appendix B).[3]

Risk perception and coping appraisal are key influencers in the private adaptation decision process. This explains why many studies use PMT to explain flood adaptation decision-making (e.g., Erdlenbruch and Bonté, 2018; Grothmann and Reusswig, 2006; Koerth et al., 2013; Noll et al., 2022). The PMT was originally developed in psychology to conceptualize protective decisions under risk (Rogers, 1975; Rogers and Prentice-Dunn, 1997), has been applied to natural disasters for nearly two decades (Bubeck et al., 2018; Grothmann and Reusswig, 2006; Noll et al., 2022), and is considered the mainstream theory to explain individual CCA behavior (van Valkengoed and Steg, 2019). The threat appraisal concerns the evaluation of rational assessment of risk (perceived probability and damages) and affect (worry or fear), i.e. how "bad" the outcomes will be, especially if no action is taken against the threat. The coping appraisal considers adaptation responses (i.e., how the threat's impact can be reduced and if one feels capable of taking the necessary actions). In case of flood adaptation, "threat appraisal" consists of worry, perceived probability, and expected damage of a potential flood; whereas the "coping appraisal" includes perceived costs of

[1] We performed a sensitivity analysis with the increased number of agents – from 1000 to 45 000. Scaling up the model in terms of the number of agents produced qualitatively the same results. Hence, to reduce computational costs across the around 37 000 runs utilized here, we present the results for 1000 agents.

[2] https://yougov.co.uk

[3] Not all measures considered lead to direct damage reductions. However, the experience gained when taking these measures is considered in the decision-making function when households try to take other measures. More information in the Supplementary Material.

adaptation measures, general outcome efficacy, and household-specific self-efficacy of implementing them, contingent also on past experience with implementing other measures. Furthermore, past flood experiences play a role.

The influence of threat and coping appraisal is derived empirically from the survey data, based on the relation between the intention to take measures in the very near future and perceptions and other adaptation constraints, including social influence, as observed in the survey data. Using logistic regression, we estimate how the probability that a household takes a specific CCA measure is driven by behavioral, economic, and social factors. Specifically, the logistic regression takes the agents' threat and coping appraisal, flood experiences, and the already undergone measures into account (see Supplementary material reporting the technical model description, i.e. ODD). Agents start with the empirical function at initialization and adapt it in the course of the simulation. Each time step, the probability of a household intending each of the ten CCA measures is updated based on evolving social norms and possibly an information policy, as well as their taken measures. Households also check whether they can afford to take a certain measure: they accumulate savings (each period they save a fraction of their monthly income) that need to be more than the costs of a measure (see Appendix B for the costs of each measure).

Depending on the household agent's location within the County (located on residential buildings as documented in OpenStreetMap (OSM contributers, 2017)), they can experience flooding associated with a 1% (*F-1:100*) or 0.2% (*F-1:500*) Annual Exceedance Probability (AEP) precipitation event, or a Harvey-like precipitation event, which we assume to be approximately equivalent to a 0.001% (F-1:10000) AEP event over the model domain (Van Oldenborgh et al., 2017) (Fig. 2). Extreme events like hurricane Harvey, are expected to occur more due to climate change, and serve here as a benchmark hazard for CCA. We have generated the flood depths and extents for each event using the Super-Fast INundation of CoastS (SFINCS) model (Leijnse et al., 2021) SFINCS has been previously applied to simulate flooding in several urban and coastal areas globally (Eilander et al., 2023; Grimley et al., 2023; Nederhoff et al., 2023), including for Houston, Texas after Hurricane Harvey (Sebastian et al., 2021). For additional details on the model setup and derivation of the precipitation events see the supplementary materials.

We adopt the standard approach to estimate property damages for each household in the ABM using the flood model depths and depth-damage curves for North America (Huizinga et al., 2017). Given our research questions, we do not simulate a flood occurrence here. Instead, each household agent assesses their individual potential flood damage for the different flood scenarios (F-1:100, F-1:500, F-1:10000) to help them assess the benefits of private CCA and to estimate individual residual damages. Namely, if a household invested in a certain CCA at time step t, in time step t + 1 their flood damage is reduced in a proportional reduction process depending on the effectiveness of the measure they chose to take (see Appendix B for the effectiveness of each measure, and Supplementary Material ODD for the damage calculation).

2.1.2. *Social influence (Meso Level)*

The meso layer of the ABM integrates varying social influences (Fig. 1). We define social influence as the combination of social network structure and the opinion exchange within it. Data on the exact connectivity of social networks relevant for CCA discussion is hardly existent, yet the network structure – i.e. with whom households exchange opinions – might matter for the diffusion of private flood adaptation. To systematically test the effect of social influence on private CCA behavior and residual damages, we compare simulations with no interaction among the household agents (no network – NoN) to agents' interactions within three commonly-used graphs that display properties of "typical" networks: Erdös-Renyi random network (N-ER), Watts-Strogatz small-world network (N-WS), and Barabasi-Albert scale-free network (N-BA) (Lehmann and Kaufmann, 2005; Peach et al., 2022). N-ER is characterized by a homogenous structure where all nodes have a similar degree of connectivity (Erdös and Rényi, 1959). N-WS is characterized by an average path length and high clustering coefficient (Watts and Strogatz, 1998). It is similar to N-ER in terms of degree distribution, but its standard deviation is larger meaning that some nodes have more social ties than others (Peach et al., 2022) (see Fig. 1, middle). The last network considered is N-BA, with a hierarchical structure, especially in comparison to the other two (Held et al., 2015; Peach et al., 2022). Its degree distribution follows the power law asymptotically (Barabasi and Albert, 1999), leading to a few large connectivity hubs compared to the rest of the network. The three networks serve as a proxy for diverse types of social relationships varying across cultures and contexts. Besides the basic network structure defining how many others an agent exchanges opinions about risks and CCA options, we specify with what type of households an agent interacts. Namely, for a given network structure, we connect agents based on homophily along three dimensions: households are more likely to connect to each other if they have similar incomes, houses, and savings.

In the ABM, each household agent is randomly assigned to a node within the chosen network structure and exchanges opinions with their connections using the Degroot's (1974) opinion dynamics model – the model that has been foundational for various opinion dynamic models (Flache et al., 2017). The household agent's opinion is influenced by their connection's opinions, which are weighted based on social

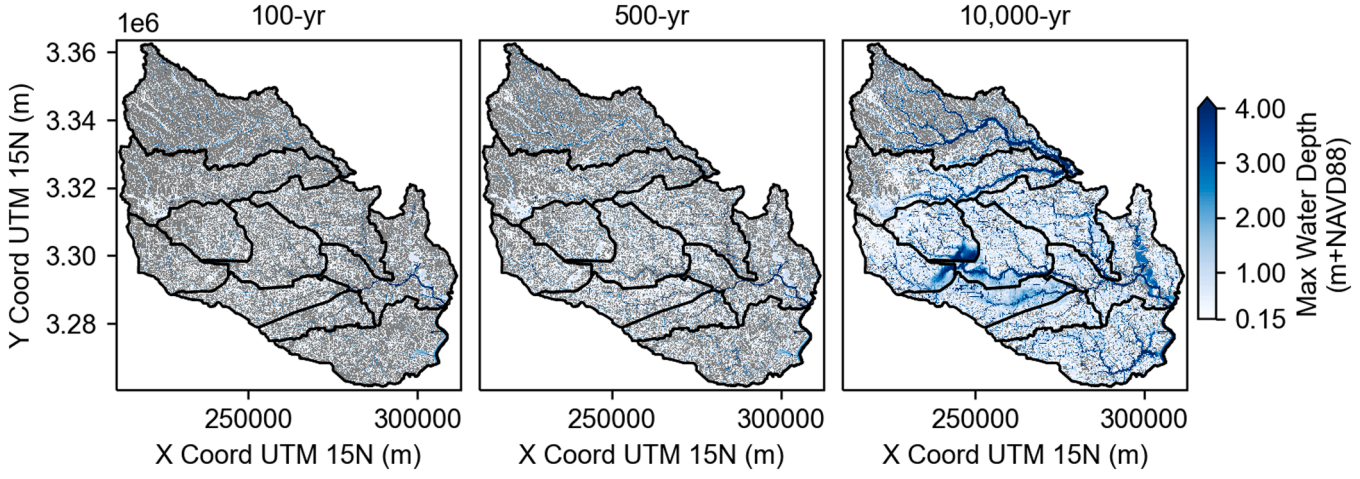

Fig. 2. Flood maps depicting the flood depths generated with the SFINCS model for the 1% annual exceedance probability (AEP) precipitation event (F-1:100, left) and 0.2% AEP precipitation event (F-1:500, middle), and a Harvey-like, or 0.001% AEP precipitation event (F-1:10000, right).

expectations as measured in the survey. According to these weights and the opinions of the connections in the social network, the household agents adjust their opinions. The information exchanged is multifaceted and links to PMT: instead of focusing on one-dimensional opinion exchange (e.g., just exchanging the decision to adapt), household agents exchange opinions on multiple items. Specifically, they can exchange information that helps appraising threats, like sharing worry (I-Worry) and perceived flood damage (I-Damage) with each other, or information that helps appraising coping strategies, like perceived costs (I-Costs) and perceived effectiveness of measures (I-Effect). We do not include the exchange on perceived probability or self-efficacy here, as these are more abstract concepts (former, Strathie et al., 2017) or less driven by opinion exchange (latter, Warner and French, 2020). We do not know what households in reality talk about most, so we test the information exchange on all four dimensions in isolation and jointly (I-All) in the ABM.

2.1.3. *Information policies (Macro Level)*

Finally, we introduce information policies that steer opinions, with the goal of nudging private CCA and risk reduction (Fig. 1, right). These information policies are usually government-led communication campaigns that provide objective information (expert-based assessment of e.g. probabilities or effectiveness of CCA measures). Information policies can be designed in a variety of ways, for example, by changing the scope of information that is spread (e.g., on risks or on solutions), by choosing whether to focus on the most severe or average hazards, and whether to engage all citizens or only those in legally defined floodplains.

To capture how information policies intervene in the opinion dynamics, we introduce an *objective* node that is connected to each household in the network. The value of the node does not change over time as it represents objective values for expected flood damage costs of different measures and their effectiveness (see Appendix C for the values communicated). We vary the *scope of the information* by testing the effect of communicating information only on threat for three different flood scenarios (P-Damage-100, P-Damage-500, P-Damage-10000), coping variables (P-Costs and P-Effect, or combined P-Coping), or a combination of these (P-All-100 (P-Coping + P-Damage-100), P-All-500 (P-Coping + P-Damage-500), P-All-10000 (P-Coping + P-Damage-10000)). Furthermore, we test what difference it makes – for CCA diffusion and damages – to get this information to every household agent (T-All) or only to select those located within the official FEMA floodplain (T-Flood) (HCFCD, n.d) as the target audience. Often, only those within the official flood zones receive risk information, but more people might benefit from the information (Rufat and Botzen, 2022; Weill, 2023). To have a clear distinction, we will talk about "opinion" for what the agents exchange with each other, and "information" for what comes from the policies.

2.2. *Design of experiments*

To assess the role of social influence and information policies on the diffusion of private CCA and the aggregate residual damages across 1000 household agents, we compare the relevant simulations to the Baseline scenario (Exp 1, Table 1). We then systematically build up our experiment by adding various forms of Social Influence (Exp 2, Table 1) and Information Policies (Exp 3, Table 1). Each of these simulations is run for 80 quarterly steps, representing 20 years. We alter different flooding scenarios, different structures of social networks, opinions about different types of information exchanged among households, and different ways to implement information policies. Our experimental setup encompasses 120 unique combinations of scenarios, each replicated 50 times, for a total of 6000 simulation experiments (excluding sensitivity analysis). Our sensitivity analysis on the number of synthetic households – increasing the population from 1000 to 10,000 and 45,000 agents – showed that results remain qualitatively the same (see Appendix G).

Table 1
Experimentation overview.

Factor	Experiment		
	Exp 1: *Baseline*	***Exp 2:*** *Social interactions*	***Exp 3****: Information Policies*
Household adaptation decision (values are initialized using survey data)	Threat Appraisal factors:		
	Worry		mean 2.29, st.d. 1.12 (1: not worried at all – 5: very worried)
	Perceived flood damage		mean 2.66, st.d. 1.23 (1: not at all severe – 5: very severe)
	Perceived flood probability		mean 4.14, st.d. 2.62 (1: completely safe – 9: flooding more than once a year)
	Coping appraisal factors:		
	Perceived effectiveness of measures m1-m10		see Appendix E for mean & st.d. of values for each of the 10 measures (m1-m10)
	Perceived self-efficacy of measures m1-m10		
	Perceived costs of measures m1-m10		
	Undergone other measures		
	Flood experience		mean 0.55, st.d. 0.50 (0: no experience, 1: experience)
Hazard probability & severity	1% AEP precipitation event (1 in 100 year flood event)		(**F-1:100**)
	0.2% AEP precipitation event (1 in 500 year flood event)		(**F-1:500**)
	0.001% AEP precipitation event (1 in 10 000 year flood event)		(**F-1:10000**)
Network structure *nr. of nodes: 1 000, see Appendix D for more information on the network properties.*	No network (**NoN**)	No network	(**NoN**)
		Erdös-Renyi random network	(**N-ER**)
		Watts-Strogatz small-world network	(**N-WS**)
		Barabasi-Albert scale-free network	(**N-BA**)
Type of information exchanged in the opinion dynamics among households	N.A.	Threat Appraisal factors:	
		Worry	(**I-Threat**)
		Perceived flood damage	(**I-Worry**)
		Coping appraisal factors:	(**I-Damage**)
		Perceived effectiveness of measures	(**I-Coping**)
		Perceived costs of measures	(**I-Effect**)
		All of the above (Coping and Threat appraisal factors)	(**I-Costs**)
			(**I-All**)
Type of the information targeted by the policy – Scope and Severity	No policy	No policy	Threat Appraisal factors: Damage for different flood severity
			100-year flood (**P-Damage-100**)
			500-year flood (**P-Damage-500**)
			10000-year flood (**P-Damage-10000**)
			Coping appraisal factors: (**P-Coping**)

(*continued on next page*)

Table 1 (*continued*)

Factor	Experiment			
	Exp 1: *Baseline*	***Exp 2:*** *Social interactions*	***Exp 3****: Information Policies*	
			Objective effectiveness of measures m1-m10	**(P-Effect)**
			Objective costs of measures m1-m10	**(P-Costs)**
			Coping appraisal factors & Damage for different flood severity:	
			Coping & 100-year flood	**(P-All-100)**
			Coping & 500-year flood	**(P-All-500)**
			Coping & 10000-year flood	**(P-All-10000)**
			See Appendix D for values communicated	
Target audience of the Information Policy - Selectivity	N.A.	N.A.	Only floodplain residents	**(T-Flood)**
			Everyone	**(T-All)**
Outcomes of interest	Residual flood damage (per household): $D_H = f_{D,H} * D_f * S$ D_H : Damage of household $f_{D,H}$: Damage factor of household $D_f = 1216.65\$/m^2$ maximum damage per square meter S: House size (m^2) (Huizinga et al., 2017; corrected for inflation) Damage reduction (per household): $\Delta D_H = D_{H,no\ adapt} - D_{H,adapt}$ $D_{H,no\ adapt}$: Damage of household before taking adaptation measures $D_{H,adapt}$: Damage of household after taking adaptation measures Aggregate Residual flood damage (total): $D_{total} = \sum_{i+1}^{n} D_{H,i}$ n: number of households Adaptation diffusion: structural measures taken over time across agent population as a percentage of all structural measures that could be taken (5 per household). Adaptation hindrance: times a household would have taken a measure according to their PMT but could not because of lack of finances.			

To address our research questions, we trace the influence of this array of different factors on the outcomes of interest: adaptation diffusion, adaptation hindrance, residual flood damage, and total residual flood damage (see Table 1, bottom). We measure adaptation diffusion for the CCA measures as the share of households' populations adopting the five structural measures at a particular time step. Our model estimates the residual damage after a possible adaptation per household as well as for the entire region.

3. Results and discussion

3.1. Private adaptation uptake under different flood risks in the baseline scenario (Exp 1)

In the Baseline Scenario (Exp 1), we examine residual damages under three flood scenarios: F-1:100, F-1:500, and F-1:10000 without social influence or information policy. As expected, the total potential damages for more severe floods (F-1:10000) are greater than those for smaller events (F-1:100). However, Fig. 3 demonstrates that there are some outliers – household agents who could potentially experience very high damages (maximum residual flood damage around $220,000) regardless of the size of the flood event. This could be related either to very high home values, and consequently high potential losses for exposed households, or because the synthetic population could end up locating in residential areas with very high hazard exposure. In either case, our analysis focuses on the uptake of CCA decisions as impacted by social influence and information policies, hence it is the adaptation diffusion and the corresponding changes in damages that we are interested in.

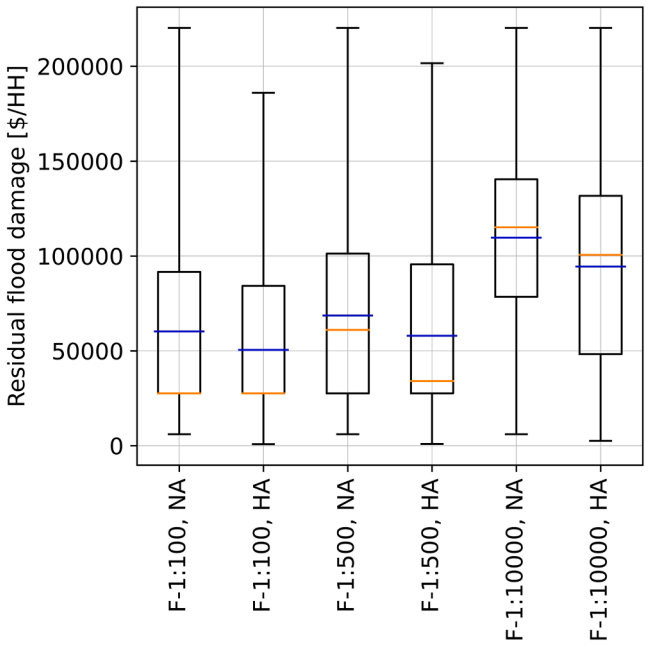

Fig. 3. Boxplot of the residual flood damage D_H (Exp1) for the three flood scenarios for both no adaptation (NA) and with household adaptation (HA) as documented in the survey. The whiskers represent the minimum and maximum of the data, whereas the box represents the interquartile range. The median of the data is plotted in orange and the mean is plotted in blue.

We report the damage with no adaptation (NA) and residual damages after household adaptation (HA) corresponding to the distribution of the reported level of CCA in our survey data. Our results show that in the absence of social influence or information policy, diffusion of private adaptation is very low. This is because household agents do not update their perceptions about the hazard, there is no learning and, hence, very little reconsideration of an adaptation decision. Nonetheless, the HA adaptation reduces the residual damage across all flood scenarios (Fig. 3).

Incorporating adaptation patterns from our survey data, leads to the decrease of the average residual damage per household by $9750 for the F-1:100 event, $10,700 for the F-1:500 event, and $15,200 for the F-1:10000 event as shown by the difference between the blue lines for the NA and HA scenarios (Fig. 3). Furthermore, the maximum damage for F-1:100 and F-1:500 is lower, so are the median damages for F-1:500 and F-1:10000. This shows that even moderate uptake of private adaptation measures can have a positive impact in reducing the worst damages. In the F-1:10000 scenario, the median of the residual damage is more than three times higher than in the other two HA scenarios, reflecting how much more severe the flooding was during Hurricane Harvey (0.001% AEP) compared to a 1% (F-1:100) or 0.2% AEP (F-1:500) precipitation event (Fig. 3, orange line).

It needs to be noted that we only consider a relatively short time span (~20 years). We do not account for the decay of adaptation measures nor consider effects of taking measures on the threat or coping appraisal. Furthermore, we do not allow for the possibility of taking multiple

measures at once. This could lead to an over- or underestimation of adaptation benefits. Our sensitivity analysis showed that the trends observed across the three different flood scenarios (F-1:100, F-1:500, F-1:10000) do not vary qualitatively for Experiments 2 and 3. Therefore, in the following analysis, we will focus only on the most extreme flood event (F-1:10000).

3.2. Introducing social interaction (Exp 2)

3.2.1. Influence of opinion dynamics about risks and adaptation on aggregated damages

To answer the first research question on the influence of social dynamics on household adaptation, we test the previously introduced three common network structures N-ER, N-WS, and N-BA with five different types of opinion exchanged (I-Costs, I-Effect, I-Damage, I-Worry) and a combination of these (I-All) and compare it to the baseline with no adaptation. Social influence is a key element of the model, especially since the opinions of household agents only change in reaction to social influence here.

Fig. 4 shows the change in average residual flood damage for each of the different combinations of network structure and opinion exchanged compared to the baseline with no adaptation. Regardless of the network structure, the social influence leads to an average 11–15% lower residual flood damages per household (Fig. 4). The main impact stems from what is exchanged in the networks, rather than the network structure. This is probably related to the combination of a fully-connected network together with the assimilative social influence model (Flache et al., 2017).

Consistently across all network types (N-BA, N-ER, N-WS), when agents exchange opinions about perceived costs (column I-Costs, Fig. 4), we observe lower diffusion and greater damage compared to opinion dynamics about other types of information. Exchanging opinions about CCA effectiveness among household agents generally leads to the highest adaptation diffusion, and the highest damage reduction compared to the opinion dynamics about other types (I-Effect column, 15% damage reduction to no measures taken, Fig. 4). This is confirmed when considering the average residual damages of those who have taken at least one structural CCA measure with those who have not (I-Effect, Table 2): the adapted household agents experience on average $5904 to $6166 less damage when they interact on effectiveness of measures alone (I-Effect) or in combination (I-All) (Table 2) and above $5000 when exchanging opinions on perceived flood damages (see I-Damage, Table 2). Notably, our results indicate that regardless of the structure of the social network, the CCA diffusion and the benefits of private CCA are the greatest if households exchange opinions about effectiveness or damages. Instead, when household agents influence each other in aspects of perceived costs of adaptation or worry (I-Costs, I-Worry), the uptake of CCA drops (Fig. 4) as do the benefits of private CCA (Table 2).

Table 2
Residual flood damage for households D_H under opinion dynamics in various social networks at the end of the simulation. Households who adapted (took a minimum of one structural adaptation measure) compared to those who did not. The results present averages across 50 Monte Carlo runs for the extreme flood scenario (F-1:10000).

		Residual damages for an average household, D_H, [$/HH]		
Interactions in the social network	Information exchanged	Adapted	Not adapted	Benefits of private adaptation (difference)
Exp 2: N-BA	I-Costs	98,005	100,636	2631
	I-Effect	93,532	99,651	6119
	I-Damage	94,431	99,665	5234
	I-Worry	96,971	99,988	3017
	I-All	**93,996**	**99,961**	**5965**
Exp 2: N-ER	I-Costs	97,971	100,718	2747
	I-Effect	93,689	99,715	6026
	I-Damage	94,541	99,646	5104
	I-Worry	97,104	100,189	3086
	I-All	**94,071**	**99,975**	**5904**
Exp 2: N-WS	I-Costs	97,922	100,780	2858
	I-Effect	93,678	99,844	6166
	I-Damage	94,851	99,865	5014
	I-Worry	97,241	100,337	3096
	I-All	**94,202**	**100,170**	**5969**

On what perceptions households are influenced determines their adaptation uptake. Nonetheless, there are other factors that could influence individuals' perceptions, for example, flood experience (Wachinger et al., 2013). Data on how risk and adaptation perceptions change is scarce; if available only over relatively short periods, and does not show significant shifts (Bubeck et al., 2020; B. L. Noll, 2023). This could influence the adaptation uptake and should be investigated.

3.2.2. Distribution of damages across households with different incomes

In addition to observing aggregate results, our ABM allows us to quantify the distribution of damages across households of different incomes (second research question). It is well-known that lower-income households are disproportionally affected in the event of a disaster (Hallegatte et al., 2020). Our results show that this not only concerns the damages, but also the benefits of adaptation: the damage reduction due

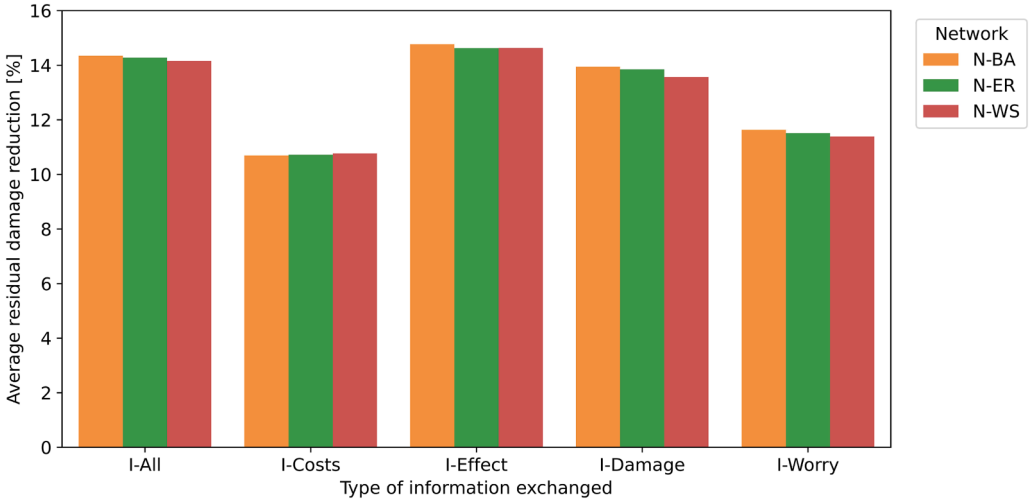

Fig. 4. Influence of social interactions on the residual flood damage D_H (percentage change compared to no adaptation) for the most extreme scenario (Exp2: F-1:10000). The results present averages across 50 Monte Carlo runs.

to private CCA is consistently greater for higher-income households (Table 3). We define 'low income' here as household agents belonging to the two lowest income quintiles as reported in the survey data; 'high income' household agents are those placed in the three upper income quintiles. Regardless of the social influence, high-income household agents reduce their damage more than low-income household agents. Especially when considering that low-income household agents may see smaller benefit returns because they have less expensive assets to protect, the differences in the benefits of private adaptation across income groups are concerning. Evidence suggests that low-income households are often located in the most hazardous areas (Collins et al., 2018) and have fewer social resources and capital to aid their recovery (Bixler et al., 2021; Liu and Mostafavi, 2023). Furthermore, in our model, the household agents' opinions are not anchored to their socio-economic background. We expect that, in reality, opinions might be distributed differently across different income groups, for example because high-income households might also be more educated or have better access to hazard or coping information which influence decisions to adapt. Even so, the observed differences in adaptation benefits in our results are striking, considering that the household agents in our model are distributed randomly across residential homes in the model domain, such that higher-income household agents are as likely to "live" in hazardous areas as lower-income households.

We observe that low-income household agents are more likely to adapt later, less often, or choose less efficient adaptation measures than high-income households. This could be related to their social capital – poorer household agents are likely connected to other poor household agents – and have fewer 'adaptation-positive' perceptions in their direct network. In our model, it is most likely driven by financial constraints – lack of sufficient income or savings. They may try to take adaptation measures but cannot due to lack of savings: average adaptation hindrance is nearly double for low-income households compared to high-income ones (Table 3). Regardless of their willingness to adapt, low-income household agents failed to adapt 3–9 times on average (rounded, Table 3 - Exp 2: N-BA, I-Costs; Exp 2: N-ER, I-Effect), whereas high-income household agents only failed to adapt 1–4 times (rounded, Table 3 - Exp 2: N-BA, I-Costs; Exp 2: N-BA or N-WS, I-Effect). This means low-income household agents are up to 280% less likely to adapt simply because of financial constraints (N-BA, I-All, Table 3).

Furthermore, we work with a monthly 5% savings rate independent of income; however, we acknowledge that lower income households may not be able to use these savings for adaptation due to other needs or due to inability to make savings because of high costs of living relative to income. We conduct a sensitivity analysis and find that the savings rate applied in the model impacts the speed at which adaptations are taken (Appendix G). Together, these findings demonstrate that even though many household agents are willing to invest in flood adaptation measures, they are held back by the lack of cash. Income and risk inequalities have been identified across different studies (Bixler et al., 2021; Hallegatte et al., 2020; Liu and Mostafavi, 2023) and are also resurfacing here. Especially reactive adaptation policies can increase the existing vulnerabilities and inequalities (Pahl-Wostl et al., 2023). Targeted policies or programs that provide subsidies to reduce the costs of adaptation – especially for lower income households that are more likely located in the at risk zones (Liu and Mostafavi, 2023) – would likely increase both the rate and number of low-income households that adapt to flooding.

3.3. Information policies (Exp3)

For the information policies we test different public communication strategies. First, we vary the selectivity of who receives the information. We examine the differences between informing everyone (T-All) and only those household agents located in the floodplain (T-Flood), considering the diffusion of information through the different network structures. Next, we vary the information scope. We test informing about coping strategies (P-Coping), containing information about the effectiveness and costs of different measures, informing about damage for different flood scenarios (P-Damage-100, P-Damage-500, P-Damage-10000) or both simultaneously (P-All-100, P-All-500, P-All-10000). As before, each of these combinations is repeated 50 times to control for the random seed number.

3.3.1. Changes in residual flood damage under various information policy designs

Information policies reduced residual damages across all model scenarios (Fig. 5); however, their benefits vary. When comparing the communication to all household agents (T-All) versus only those located in the floodplain (T-Flood), we find that informing everyone motivates them to flood-proof their homes, resulting in larger damage reductions overall. This is not surprising, as more household agents receive information about their flood exposure and coping strategies and can act upon it. With climate change, the boundaries of actual flood zones are shifting, exposing even previously safe locations to hazards (Aryal et al., 2022), so household agents located outside the official floodplain can also be at risk of flooding.

In the T-Flood setup, the damage reduction is consistently lower than

Table 3
Differences in damage reduction and adaptation hindrance (times households wanted to adapt but could not due to financial constraints) among high- and low-income households. The results present averages across 50 Monte Carlo runs for the extreme flood scenario (F-1:10000) in the presence of social influence in the three types of social networks (Exp 2).

		Average ΔD_H (for F-1:10000) [$/HH]			Average adaptation hindrance [times/HH] (out of 76 possible times)		Likelihood of low-income households not adapting compared to wealthier ones
Exp 2: Social interactions	Information exchanged	Low income	High income	Times higher	Low income	High income	
Exp 2: N-BA	I-Costs	9653	12866	1.33	2.88	1.36	112.01%
	I-Effect	11112	19251	1.73	8.62	4.43	94.34%
	I-Damage	10895	17920	1.64	7.12	3.60	97.85%
	I-Worry	9542	14627	1.53	5.19	2.25	131.12%
	I-All	12450	17644	1.42	6.31	1.68	276.34%
Exp 2: N-ER	I-Costs	9406	13108	1.39	3.04	1.49	103.83%
	I-Effect	10823	19206	1.77	8.73	4.38	99.20%
	I-Damage	10628	17937	1.69	7.20	3.54	103.38%
	I-Worry	9287	14600	1.57	5.27	2.22	137.20%
	I-All	12087	17780	1.47	6.40	1.74	268.11%
Exp 2: N-WS	I-Costs	9850	13059	1.33	3.09	1.72	79.47%
	I-Effect	11254	19105	1.70	8.53	4.43	92.29%
	I-Damage	10886	17420	1.60	6.77	3.39	99.55%
	I-Worry	9618	14320	1.49	4.94	2.18	126.45%
	I-All	12335	17563	1.42	6.23	2.14	191.20%

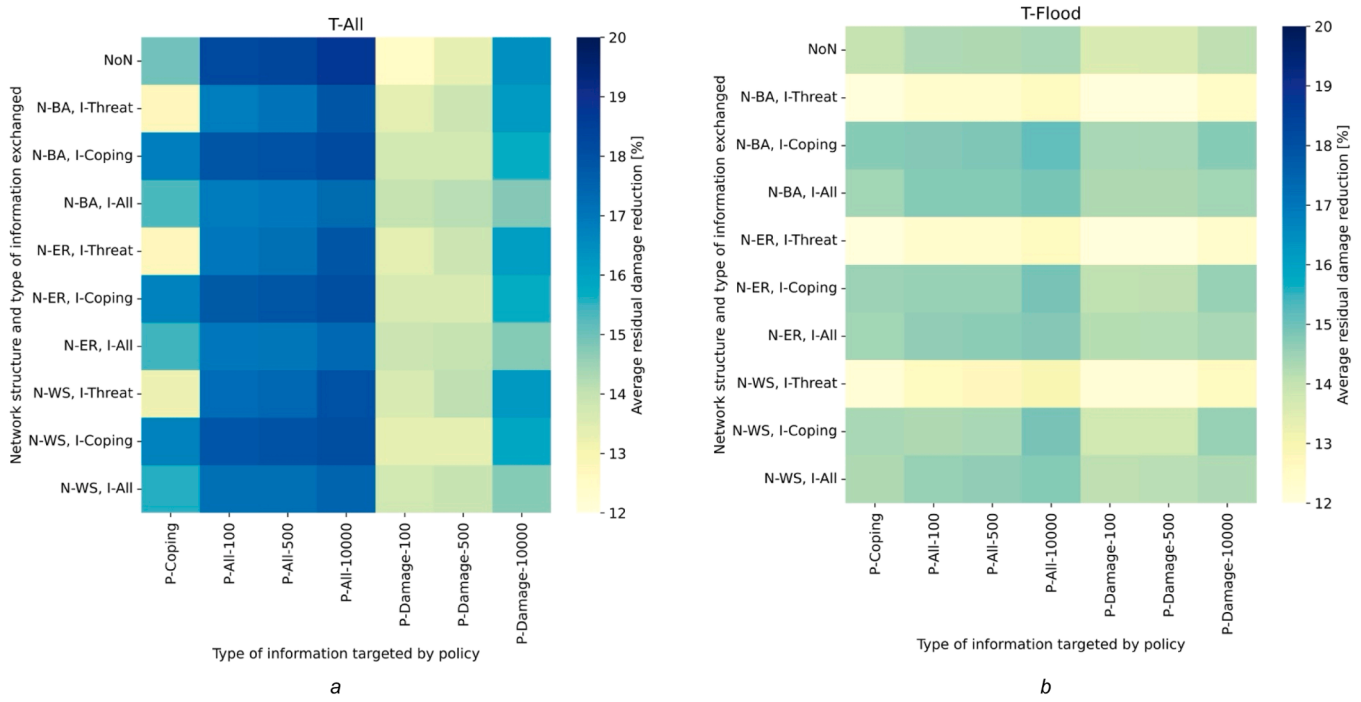

Fig. 5. Influence of information policies differentiated between targeting all (T-all, a) versus only those in the floodplain (T-Flood, b) on the residual flood damage D_H(percentage change compared to no adaptation) for the extreme-flooding scenario (Exp3: F-1:10000).

in the T-All setup. Whereas for T-All the flood damage ranges from 89,000 $/HH $\leq D_H \leq$ 96,000 $/HH (up to 19% damage reduction compared to no adaptation), for T-Flood it varies from 93,000 $/HH $\leq D_H \leq$ 97,000 $/HH (less than 15% damage reduction compared to no adaptation). The T-Flood reduces the damages less because there is no information diffusion for the no network setup (NoN), meaning that no information is passed to households outside the floodplain via social influence, Whereas for the experiments including social influence (Fig. 5: T-Flood, for N-BA, N-WS and N-ER networks), the information from the policy does not diffuse through the social network to the same extent as informing everyone would (T-All). The reduced diffusion in the social networks could be due to the limited timespan modeled, meaning that the information does not spread fast and far enough. More likely, there are interaction effects between information and opinion: the information from the policy competes with the opinions of the other household agents and is "overruled", meaning that the information does not reach far beyond those who receive it directly (those in the flood zone). This could be an artifact of how information policy is modeled.

For these information policies to be most effective, it matters what type of information is being exchanged within the social networks. For example, informing about coping strategies (P-Coping), when people only exchange information on the threat of flooding (I-Threat) is less effective than communicating about coping (P-Coping) when households also receive coping information from their network connections (I-Coping). This hints at potential synergistic effects between social influence and communication policies if they are catered to each other.

Providing people with realistic expectations on damage for the expected flooding seems to be important in reducing damages. In both P-All-10000 and P-Damage-10000 the damage reduction is higher compared to informing about less severe flooding (P-All-100 or −500, P-Damage-100 or −500).

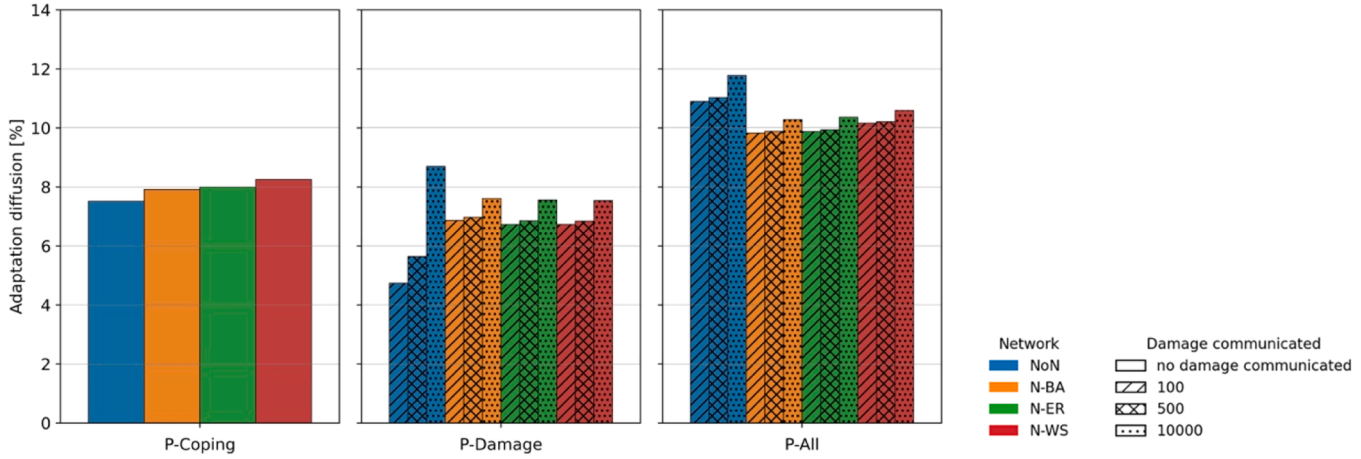

Fig. 6. Adaptation diffusion after 20 years as a share of all structural measures that could be taken (5 per HH) for different networks (NoN, N-BA, N-ER, N-WS; all I-All) and communication policies (Exp3: F-1:10000). Adaptation diffusion would be 100% if all households took all 5 structural measures. Adaptation diffusion over time in Appendix F.

3.3.2. Importance of different types of information for changing behavior and damages

Looking at what information is communicated, we see that it impacts private CCA behavior in different ways (Fig. 6). This results in a distinction in the aggregate residual flood damage between campaigns focused on informing about risk (P-Damage) or coping mechanisms (P-Coping) and those informing about a combination of the strategies (P-All), regardless of the social influence setup (Fig. 5).

Looking at the network structures, we see that without social influence the speed and scope of adaptation diffusion can be the greatest but also the least effective (NoN, Fig. 6). The objective information directly reaches the household agents and is not biased by the subjective opinions of connections, since the latter are muted. This leads to the household agents fully absorbing the information (see also Table 4 – NoN, Exp3), and acting upon it. In this setup, it is especially important what information is communicated as it influences the adaptation uptake most directly (see differences in adaptation uptake for P-Damage-100/-500/-1000 in Fig. 6b). Yet, in reality some form of social influence is always present, possibly altering the impact of information policy campaigns both in potentially positive and negative ways. Our results show that the three networks lead to similar adaptation diffusion. The policies increase the adaptation uptake over time (see Appendix F for more details), but the impact of the different information policies is less pronounced and mediated through the social influence (Fig. 6).

This is supported when we look at how the perceived flood damage varies between the no network setup (NoN) in comparison to the other three networks (N-BA-N-ER, N-WS; Table 4). While the comparability of the flood damage factor as proposed by Huizinga et al. (2017) and the perceived flood damage could be questioned, household agents in this study tend to either overestimate (Table 4 – NoN, Exp 1: 0.52) or underestimate (Table 4 – N-BA//N-ER/N-WS, I-All, Exp 2: 0.43) the flood damage for the F-1:10000 scenario. The information policies in Exp 3 (P-Damage-100/-500/-10000) can steer them in the "correct" direction, with this being most effective in the NoN-setup: the alignment of the communicated value of P-Damage with the perceived flood damage is very high at end (Table 4, NoN, Exp3), whereas for the other networks there always remains a gap between average perceived damage and the communicated damage (Table 4, N-BA/N-ER/N-WS, Exp3).

Reflecting on this diversity of social influences, it is important to consider that running risk information campaigns is intensive, and its success depends on a wide range of factors (Kellens et al., 2013). For example, if a Harvey-like flood were to occur again (F-1:10000), informing households about the potential damages resulting from a 1% or 0.2% AEP event (P-Damage-100, P-Damage-500) would lead them to underestimate their flood risk (Table 4: F-1:10000 risk is 0.52, risk communicated (P-Damage-100, P-Damage-500) lower).

Table 4
Mean objective vs perceived flood damage for the 0.001% AEP scenario. We compare the experiments with no policy (Exp 1 and Exp 2) with the policy experiment (Exp 3) for the different social interaction setups (NoN; N-BA/N-ER/N-WS, I-All). We compare the communicated damage factor (Communicated value (P-Damage) for three different communication scenarios (Exp 3: P-Damage-100, −500, and −10000)) with the perceived flood damage of the households (Perceived flood damage at t_{end}). Each household has an individual flood damage factor based on their location; they receive this personalized information. Here, the means over all the households are shown.

		Perceived flood damage at t_{end}		
		Exp 3: P-Damage-100	Exp 3: P-Damage-500	Exp 3: P-Damage-10000
Flood risk (F-1:10000)			0.52	
Communicated value (P-Damage)		0.28	0.32	0.52
NoN	Exp 1		0.52[9]	
	Exp 3: P-Damage	0.30	0.34	0.54[10]
N-BA, I-All	Exp2		0.43	
	Exp 3: P-Damage	0.35	0.37	0.48
N-ER, I-All	Exp2		0.43	
	Exp 3: P-Damage	0.34	0.37	0.49
N-WS, I-All	Exp2		0.43	
	Exp 3: P-Damage	0.33	0.36	0.50

[9]This equals the starting perceived flood damage for all scenarios
[10]That this is higher than the communicated value of P-Damage-10000 could be due to rounding when calculating the influence of the policy on the household agents' opinion

3.4. Cumulative effect of private adaptations for regional damages

Estimates of property damage caused by Hurricane Harvey vary. The Harris County Flood Control District estimated that 154,170 properties, or about 9–12% of the total buildings in Harris County, flooded during Hurricane Harvey (HCFCD, 2018). Extrapolating from our 1000 simulated households to the about 150,000 that were affected in Harris County, we estimate roughly $15 billion in total property damages for the Harvey-like scenario if no further private CCA is undertaken (F-1:10000) (Table 5 – Cumulative residual flood damage, t_{Start}). Our model suggests that household adaptation following social influence alone can reduce this damage by up to $1 billion (Table 5 – Cumulative damage reduction, Exp 2), and that with appropriate information policy, damages can be further reduced by almost $1.8 billion (Table 5 – Cumulative damage reduction, Exp 3). Importantly, uptake of private adaptation occurs from the bottom-up, is cost-effective, and aligns with individual opinions and social norms.

The positive effects of social influence and information campaigns cumulate and significantly reduce the damage. Nonetheless, they cannot prevent damages entirely. Private adaptation decisions are one important element in CCA; and public information policies are one example of how successful adaptation across scales can be promoted. To close the adaptation gap, adaptation actions need to be increased massively and across all scales, from local governments and private stakeholders to the international climate policy (Magnan et al., 2023).

4. Conclusion

This article presented a systematic investigation into the role of social influence and information policies on private property-level adaptation decisions and eventual aggregate regional damage reduction. We systematically tested the impact of different network structures and information policies on household decisions to adapt their homes to flooding and estimated the associated benefits in terms of damage reduction. We employed empirical survey data and simulated flood inundation data from Harris County, Texas, USA, to develop an ABM of household CCA behavior, investigating policy effectiveness given the interplay of individual and social processes.

Even though we only look at a confined geographic region and a selection of ten private property-level adaptation measures, some general conclusions can be drawn. We found that the type of information (e.g. on damages, worry, costs or effectiveness of measures) about which opinions are exchanged in this social network has a substantial effect on the adaptation diffusion and, ultimately, residual regional damages (10–15% damage reduction compared to not taking measures), with lower income households consistently being less likely to adapt. Despite the latter, this is good news for the information policy design, as it suggests that across different social network structures – which could vary across cultures – it is the type of information that is most influential in tilting individual opinions and leading or not to the massive uptake of household-level CCA measures. Information policies can further support private adaptation. Given the empirical behavioral patterns elicited via survey and studied dynamically across space and time in our ABM, we

Table 5
Damage comparison for household D_H and total damages D_{total} (150 000 affected property (i.e., households) in Harris County (United States Census Bureau, 2022) – interpolated from mean residual flood damage).

			Residual flood damage D_H [$/HH]		Cumulative residual flood damage D_{total} [billion$]		Cumulative damage reduction [billion$]
Experiment	Social Influence	Policy	t_{Start}	t_{End}	t_{Start}	t_{End}	$D_{total,\ t_{Start}} - D_{total,\ t_{End}}$
Exp 1	NoN		100,982	94,440	15.15	14.17	0.98
Exp 2:	N-BA, I-All		100,976	93,996	15.15	14.10	1.05
	N-ER, I-All		100,993	94,071	15.15	14.11	1.04
	N-WS, I-All		101,103	94,202	15.17	14.13	1.04
Exp 3:	NoN	P-Coping, T-All	100982	93310	15.15	14.00	1.15
		P-Damage-10000, T-All	100982	91766	15.15	13.76	1.38
		P-All-10000, T-All	100982	89140	15.15	13.37	1.78
	N-BA, I-All	P-Coping, T-All	100,976	92,931	15.15	13.94	1.21
		P-Damage-10000, T-All	100,976	93,492	15.15	14.02	1.12
		P-All-10000, T-All	100,976	90,726	15.15	13.61	1.54
	N-ER, I-All	P-Coping, T-All	100,993	91,115	15.15	13.67	1.48
		P-Damage-10000, T-All	100,993	93,533	15.15	14.03	1.12
		P-All-10000, T-All	100,993	90,702	15.15	13.61	1.54
	N-WS, I-All	P-Coping, T-All	101,103	92,605	15.17	13.89	1.27
		P-Damage-10000, T-All	101,103	93,577	15.17	14.04	1.13
		P-All-10000, T-All	101,103	90,533	15.17	13.58	1.59

observe that public communication targeting coping and risk appraisal of households simultaneously (informing about costs/effectiveness of the different adaptation measures plus the avoided private damages) appears to be most successful in reducing the expected overall damages in the region further (20% decrease). The pitfall with spreading information only about risks (like expected damage for different flood scenarios) is that it might lead to either people misperceiving private risks or behavioral paralysis due to anxiety in the absence of actionable pathways, both leading to less household (private) adaptation and greater damages during more extreme events, such as Hurricane Harvey.

Our findings have direct implications for the design of CCA policies. Though several studies recommend public information provision as an intervention for CCA, few pay attention to the design of these interventions. Here, we found that different characteristics of information policy—including its scope, selectivity, and severity—are likely to influence policy effectiveness. For instance, including coping information like costs and effectiveness of adaptation measures makes the information policy consistently more effective than just spreading risk information. It is also important that the information is provided to all rather than only to those at highest risk. Further, we suspect that the effectiveness of information policy may vary depending on the social network configuration and what is exchanged within it (and is thus likely to be more context-dependent than assumed in existing research). Future work would need to examine this further, especially the role of different opinion dynamics models on the emergence of behavior, and what realistic network configurations and information exchange would be for this empirical setting. Specifically, the network structure and informal information exchange may vary significantly across locations and cultures. We need to study what kind of people are influential, how people connect to each other, if homophily in terms of income or education or other characteristics plays a role, and how frequent or intense the exchange is (i.e., how much people are influenced in their opinion). At the same time, existing vulnerabilities and inequalities need to be recognized. Furthermore, we need to understand what impact other institutions (e.g., media, governmental institutions, norms (Davidson et al., 2024)) have on people's CCA beliefs – the information policy used here is only a first attempt at this. And lastly, private CCA is only one piece in the bigger picture of CCA that needs to happen across multiple scales – there is a need to advance the understanding of the interplay between public and private action.

CRediT authorship contribution statement

Thorid Wagenblast: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Tatiana Filatova:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Lauren Grimley:** Writing – original draft, Methodology. **Antonia Sebastian:** Writing – review & editing. **Nihit Goyal:** Writing – review & editing, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2026.104393.

Appendix

List of measures

List of adaptation measures asked about in the survey:

Measure	Explanation
S1*	Raising the level of the ground floor above the most likely flood level
S2*	Strengthen the housing foundations to withstand water pressures
S3*	Reconstructing or reinforcing the walls and/or ground floor with water-resistant materials
S4*	Raising the electricity meter above the most likely flood level or an upper floor
S5*	Installing anti-backflow valves on pipes
S6	Installing a pump and/or one or more system(s) to drain flood water
S7	Fixing water barriers (e.g., water-proof basement windows)
NS1*	Keeping a working flashlight and/or batter-operated radio and/or emergency kit in a convenient location
NS2	Purchasing sandbags, or other water barriers
NS3	Buying a spare power generator to power your home
NS4	Being an active member in a community group aimed at making the community safer
NS5*	Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do
NS6	Installing a refuge zone, or an opening in the roof of your home or apartment
NS7*	Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage
NS8	Asking someone (local government, Civil Defense, etc.) for information about what to do in case of emergency
NS9	Asking/petitioning government representative to increase the public protection measures
NS10*	Storing emergency food and water supplies
NS11*	Moving/ storing valuable assets on higher floors or elevated areas

* Included in this study (5 most commonly implemented structural and non-structural adaptation measures)

Costs and effectiveness of adaptation measures

Table B1
Costs and effectiveness for different private adaptation measures. Estimates mainly from Aerts (2018) and Kreibich et al. (2015), adjusted for 2020 inflation. Non-structural measures mainly aim at reducing bodily harm – not quantified for this study. For each household, a random number is drawn from the range of costs and measures which reflect their individual costs and benefits for adapting

Measure	Cost	Damage reduction
S1	$33–70k	0% - flood height reduced
S2	$9–15k	30–50%
S3	$2500–9000	15–45%
S4	$2500–5000	30–40%
S5	$2600–3300	15–35%
S6	$900–7000	10–30%
S7	$9–23k	10–85%
NS1	$10–30	0%
NS2	$45–220	30–60%
NS3	$450–700	0%
NS4	$5–15	0%
NS5	$0	0%
NS6	$800–1500	0%
NS7	$0	0%
NS8	$0	0%
NS9	$0	0%
NS10	$100–200	0%
NS11	$0	0%

Information policy - communicated values

The values that can be communicated are the costs and effectiveness of adaptation measures, as listed in Table C1, and the flood damage. The flood damage communicated is the flood damage factor derived from the flood depth according to Huizinga et al. (2017) for each household given a certain flood map.

Table C1
Costs and effectiveness of measures as communicated with the information policy. Highest cost/effectiveness as documented in Appendix B set to 1, rest relative to that

Measure	Communicated cost (0−1)	Communicated effectiveness (0−1)
S1	0.878	1
S2	0.750	0.842
S3	0.359	0.632
S4	0.234	0.737
S5	0.184	0.526
S6	0.247	0.421
S7	1	1
NS1	0	0
NS2	0.002	0.947
NS3	0.010	0
NS4	0	0
NS5	0	0
NS6	0.020	0
NS7	0	0
NS8	0	0
NS9	0	0
NS10	0.003	0
NS11	0	0

Network properties

The networks are generated with the following properties:

- Erdös-Renyi random network (N-ER):
  - probability of edge creation p = 0.0005
- Watts-Strogatz small-world network (N-WS):
  - nearest neighbors: k = 5
  - probability of rewiring edge = 0.5
- Barabasi-Albert scale-free network (N-BA):
  - number of edges to new node m = 3

Data household adaptation decision

Table E1
Description other variables important for Household Decision Making

	Perceived effectiveness (1: extremely ineffective – 5: extremely effective)		Perceived self-efficacy (1: I am unable – 5: I am very able)		Perceived costs (1: very cheap – 5: very expensive)		Undergone (0: no, 1: yes)	
Measure	Mean	Std	Mean	Std	Mean	Std	Mean	Std
S1	3.35	1.37	1.91	1.30	4.41	1.02	0.09	0.29
S2	3.16	1.32	2.16	1.38	4.30	0.95	0.07	0.25
S3	3.17	1.29	2.25	1.37	4.18	0.98	0.08	0.26
S4	3.29	1.27	2.50	1.48	3.54	1.19	0.12	0.32
S5	3.24	1.27	2.50	1.45	3.63	1.17	0.07	0.26
NS1	3.82	1.39	4.46	1.10	1.84	1.22	0.74	0.43
NS5	3.44	1.24	3.54	1.33	2.00	1.23	0.28	0.45
NS7	4.12	1.15	4.18	1.19	2.11	1.32	0.59	0.49
NS10	4.01	1.20	4.34	1.04	2.62	1.17	0.50	0.50
NS11	4.10	1.16	3.93	1.38	2.25	1.34	0.44	0.50

F. Adaptation diffusion over time

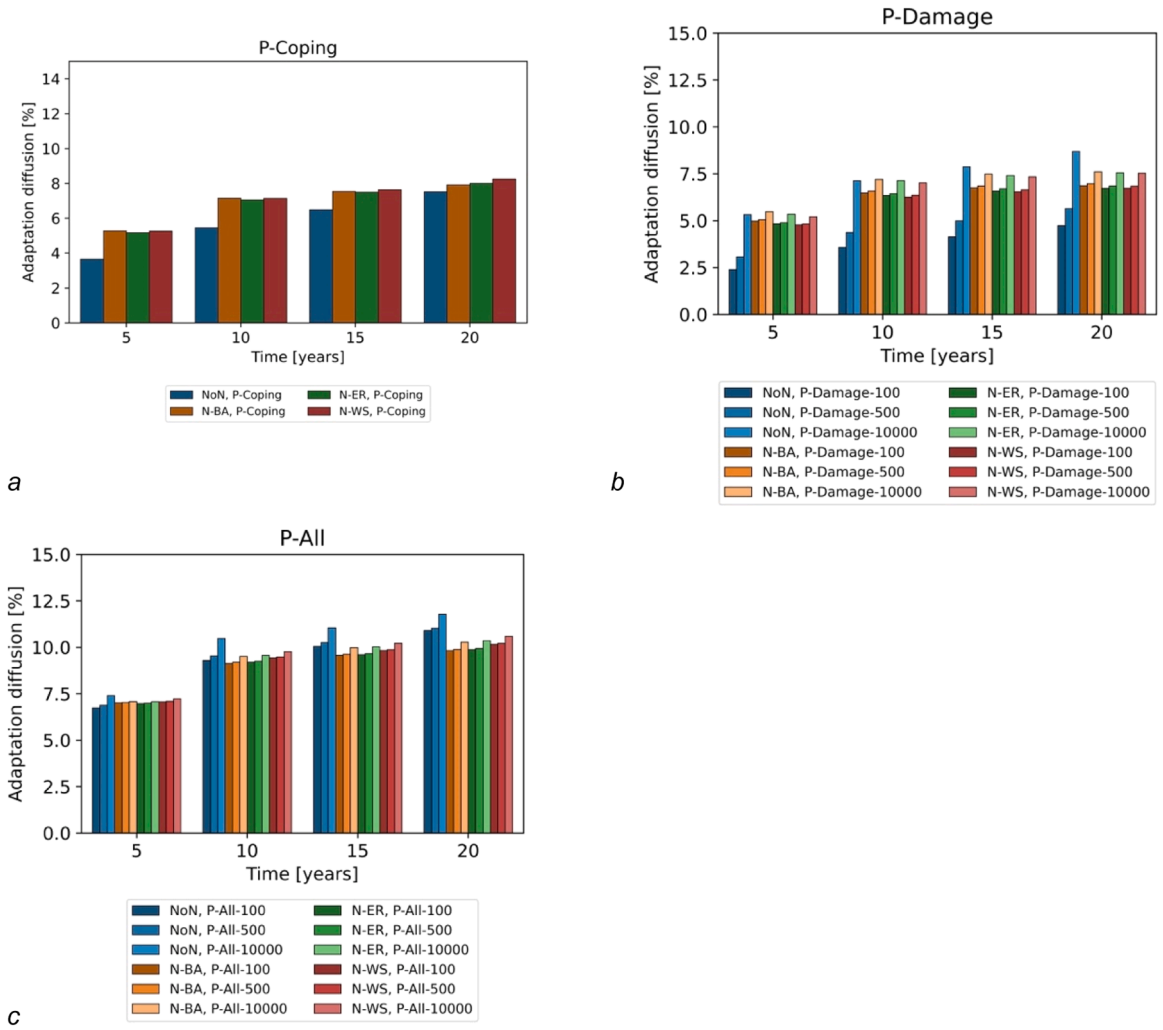

Figure F1. Adaptation diffusion as a share of all structural measures that could be taken (5 per HH) for different networks (NoN, N-ER, N-WS, N-BA; I-All) and communication policies (P-Coping (a), P-Damage (b), P-All (c)) (Exp3: F-1:10000). Adaptation diffusion would be 100% if all households took all 5 structural measures

G. Sensitivity analysis

The sensitivity analysis was performed over the different network parameters, savings rate, the frequency of taking adaptation measures and the weight assigned to a household's own opinion in the social interaction. An overview of the parameters and the values used and tested is found in Table F1.

Table F1
Parameters for the sensitivity analysis

	Variable (as in model)	Default value	Values sensitivity
Number of households	Nr_households	1000	10 000, 45 000
Network-related	Probability_of_network_connection	0.4	0.1, 0.3, 0.6
	Number_of_edges	3	1, 2, 4, 7
	Number_of_nearest_neighbours	5	1, 3, 7, 10
Savings rate	Savings_rate	0.05	0, 0.01, 0.1, 0.2
Frequency of taking measures	Pause_after_last_measure	2	0, 2, 10, 20
Weight assigned to own opinion	Basic_own_trust	0.5	0, 0.25, 0.8, 1

Looking at the difference between the simulation with 1, 10, or 45 thousand household agents. Due to the longer runtime with more agents, we compare 5 runs each (see Table F2). The difference in means is very small. Due to the massively increasing runtime with more agents, we decide to run the simulation with 1000 household agents.

Table F2
Difference between choosing different numbers of household agents (nr_households). Absolute percentage difference shown exemplary for mean residual flood damage and perceived flood damage at the end of the simulation

	NoN		N-BA		N-ER		N-WS	
	Residual flood damage	Perceived flood damage	Residual flood damage	Perceived flood damage	Residual flood damage	Perceived flood damage	Residual flood damage	Perceived flood damage
Difference 1000–10,000 (abs)	1.10%	1.32%	1.03%	1.68%	1.58%	0.76%	1.70%	0.15%
Difference 10,000–45,000 (abs)	0.37%	0.68%	0.21%	1.00%	0.13%	0.70%	0.10%	0.70%

The network parameters do not influence the general trend of the residual flood damage but rather shift the results slightly up and down (Figure F1).

The time household agents need to pause before taking another measure has a significant impact on the speed in which adaptation is taken up and hence the damages are reduced (Figure F2). The shorter the pause, the faster the damages drop, but the faster an equilibrium seems to be reached – everyone who wanted to take a measure did so. Whereas if they are only allowed to take measures very rarely, the damages drop later or not at all,

The savings rate, so the money household agents have available to spend on adaptation measures, has a noticeable impact on how much people adapt (Figure F3). With lower savings rates, the residual damage plateaus at a higher level.

Lastly, the weight assigned to the own opinion when considering the social influence of connecting household agents matters to a certain extend (Figure F4). When households listen only to themselves (weight = 100%), the no network setting (NoN) is replicated. Apart from that, it does not seem to be critical how much new opinions are taken in, as long as there is social interaction. It needs to be considered, that this is only the base trust, but social expectations also matter. These are taken from the survey data, so in the end, the basic_own_trust is only one part of the trust people put in their own opinion (see Supplementary Material – ODD for more details).

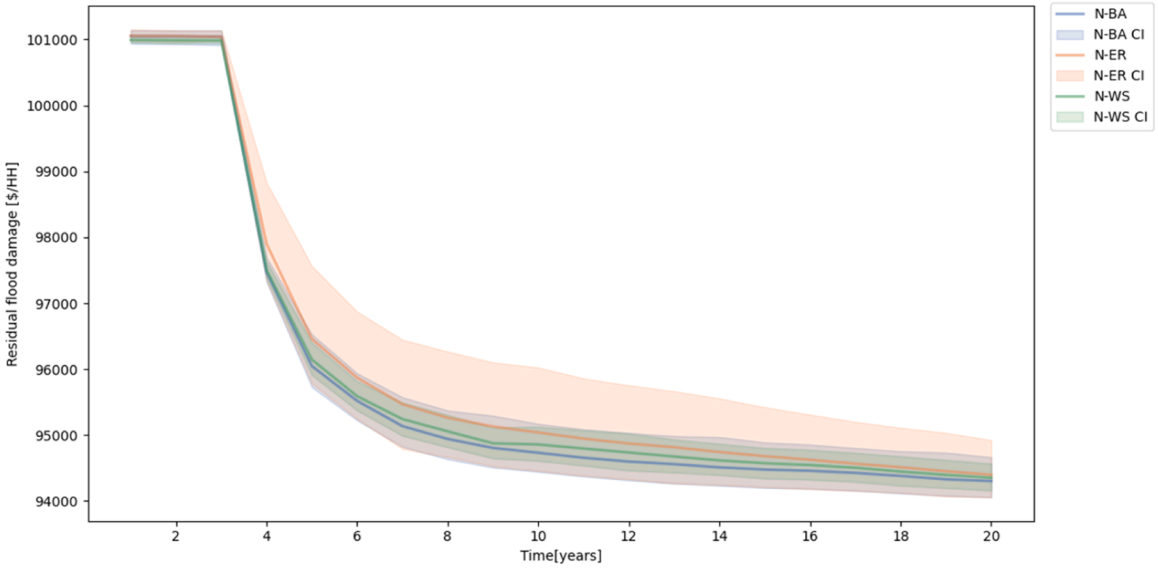

Figure G1. Sensitivity analysis on network parameters (see Table 8 for values used)

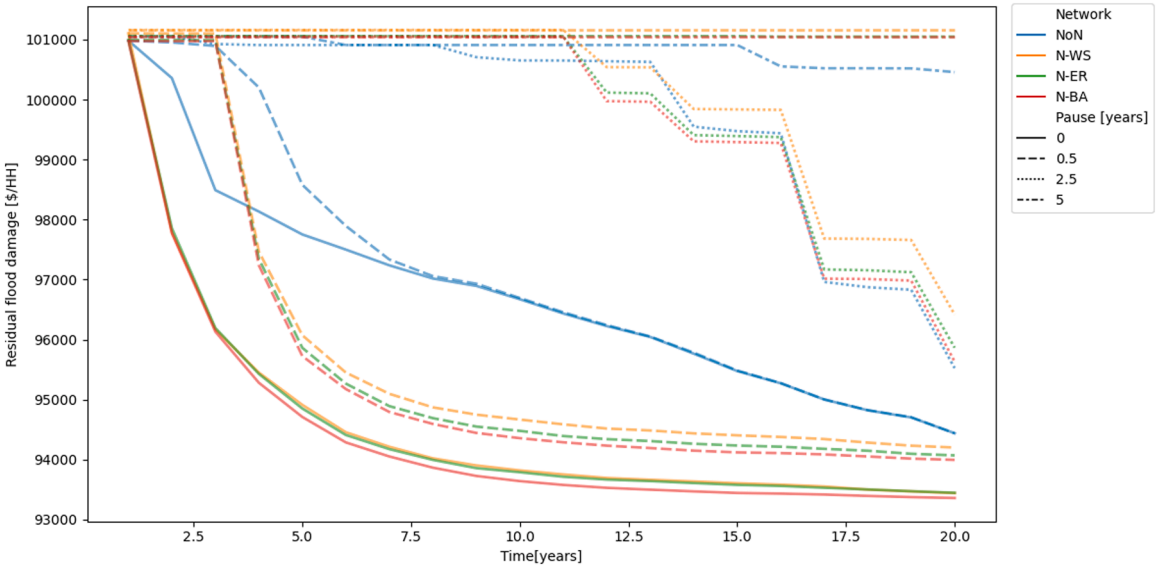

Figure G2. Sensitivity analysis on frequency of taking measure (see Table 8 for values used)

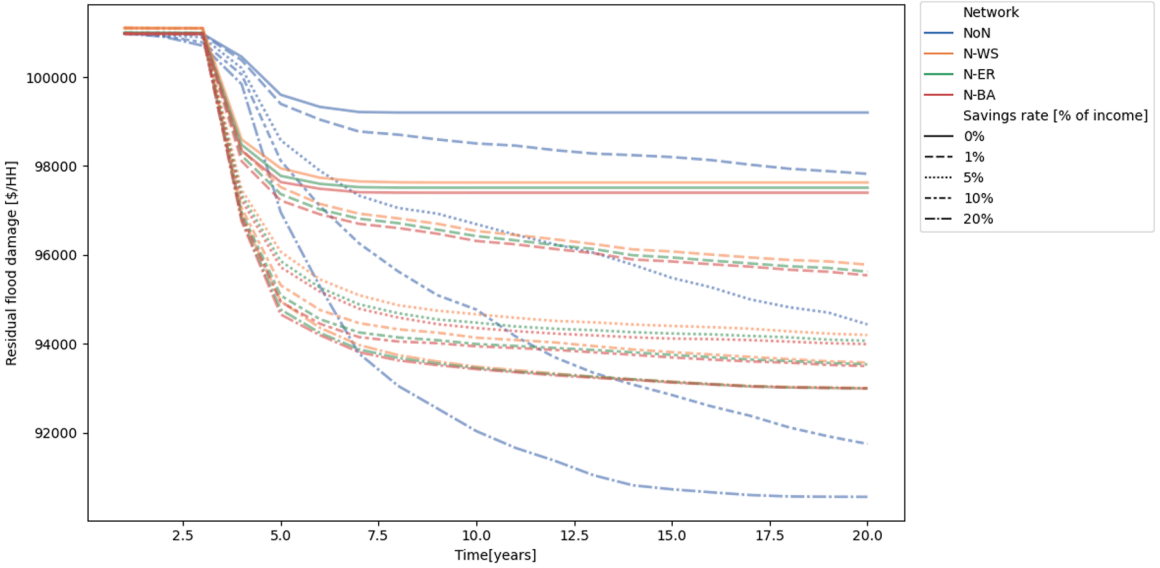

Figure G3. Sensitivity analysis on savings rate parameters (see Table 8 for values used)

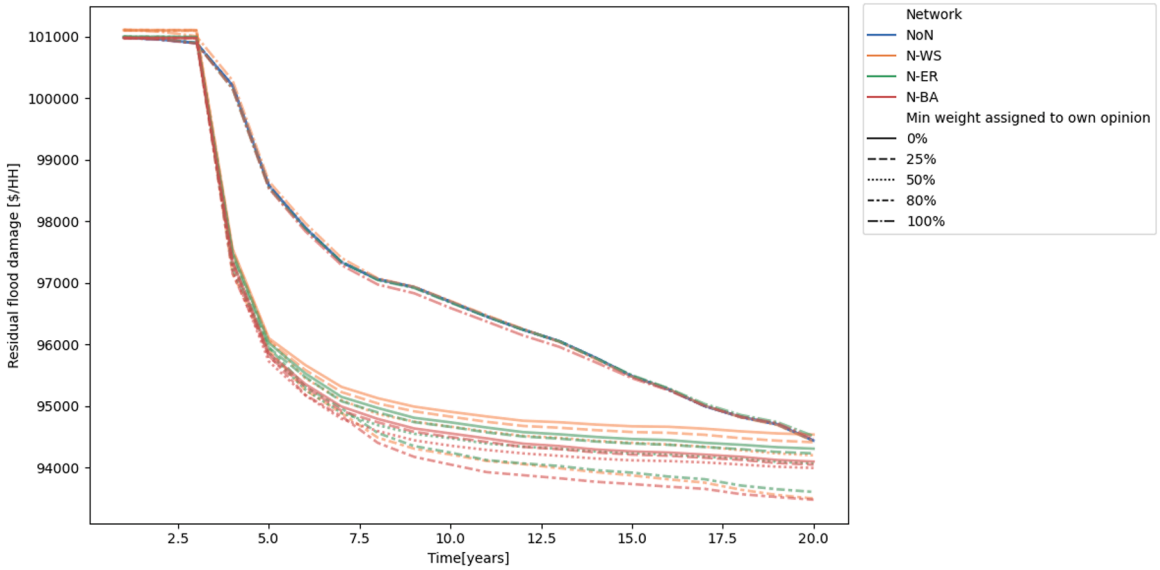

Figure G4. Sensitivity analysis on weight assigned to own opinion in network exchange (see Table 8 for values used)

Data availability

The code to replicate this work is available at: https://github.com/thoridw/SIPAABM and https://github.com/SC3-TUD.

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