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How the USA can benefit from risk-based premiums combined with flood protection

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Flood risk management in the USA is largely embedded in the National Flood Insurance Program (NFIP). Climate change and increasing exposure in flood plains pose a challenge to flood risk managers and make it vital to reduce risk in the future. The proposed reforms are steering the NFIP to risk-based premiums, but it is uncertain if the reforms will result in unaffordability and incentivize risk-reduction investments or how the NFIP is affected by large-scale adaptation efforts. Using an agent-based model approach for current and future scenarios, we demonstrate that risk-based premiums will yield a positive societal benefit (US$10 billion) because they will incentivize household risk-reduction investments. Moreover, our results show that proactive investment in large-scale adaptation measures complements a transition to risk-based premiums to yield a higher overall societal benefit (US$26 billion). We suggest that transitioning the NFIP to risk-based premiums can only be secured by additional investments in large-scale flood protection infrastructure.

Flooding is a devastating natural hazard, causing an average >US$100 billion of damage every year[1]. Recent events of coastal and river flooding in Europe and Asia have shown the huge impact of such events on communities and policy-makers are struggling with how to anticipate future increase in flood risk due to climate change and population growth[2]. Without adaptation investments under the representative concentration pathway (RCP) 4.5 and shared socio-economic pathway (SSP) 2 scenarios, fluvial flood risk for the USA is expected to increase from about US$27 billion to US$66 billion per year (refs. [3,4]), while coastal flood risk cost is expected to increase from US$1.8 billion to US$189 billion[5]. In the USA, the National Flood Insurance Program (NFIP) is the main program for managing flood risk. The NFIP provides almost 5 million policies to homeowners and businesses in the USA, covering US$1.2 trillion in assets and making it the largest flood insurance market worldwide[6]. The program requires households in a participating community with a bank-backed mortgage living within a 100-year flood zone to purchase mandatory flood insurance coverage. It also requires that new developments in these zones meet certain building codes. These low-lying flood zones are mapped by the Federal Emergency Management Agency (FEMA). However, the program has a US$20.5 billion debt due to, amongst other things, the setting of premiums on the basis of national averages that do not reflect local risk, new development in flood-impacted areas, and the lack of incentives for homeowners to implement flood adaptation measures other than building elevation[7].

Several reforms have been introduced to solve some of the issues. These include the new Risk Rating 2.0 program, which more accurately sets premiums that reflect yearly risk for individual buildings[8]. While the reforms are expected to increase mean insurance uptake and solve financial burden on the program, they are also likely to put pressure on affordability for low-income households living in high-risk flood zones. Moreover, there is uncertainty how the NFIP will perform under future climate change conditions. However, existing studies on NFIP reforms only focus on a specific region or on individual elements of the program

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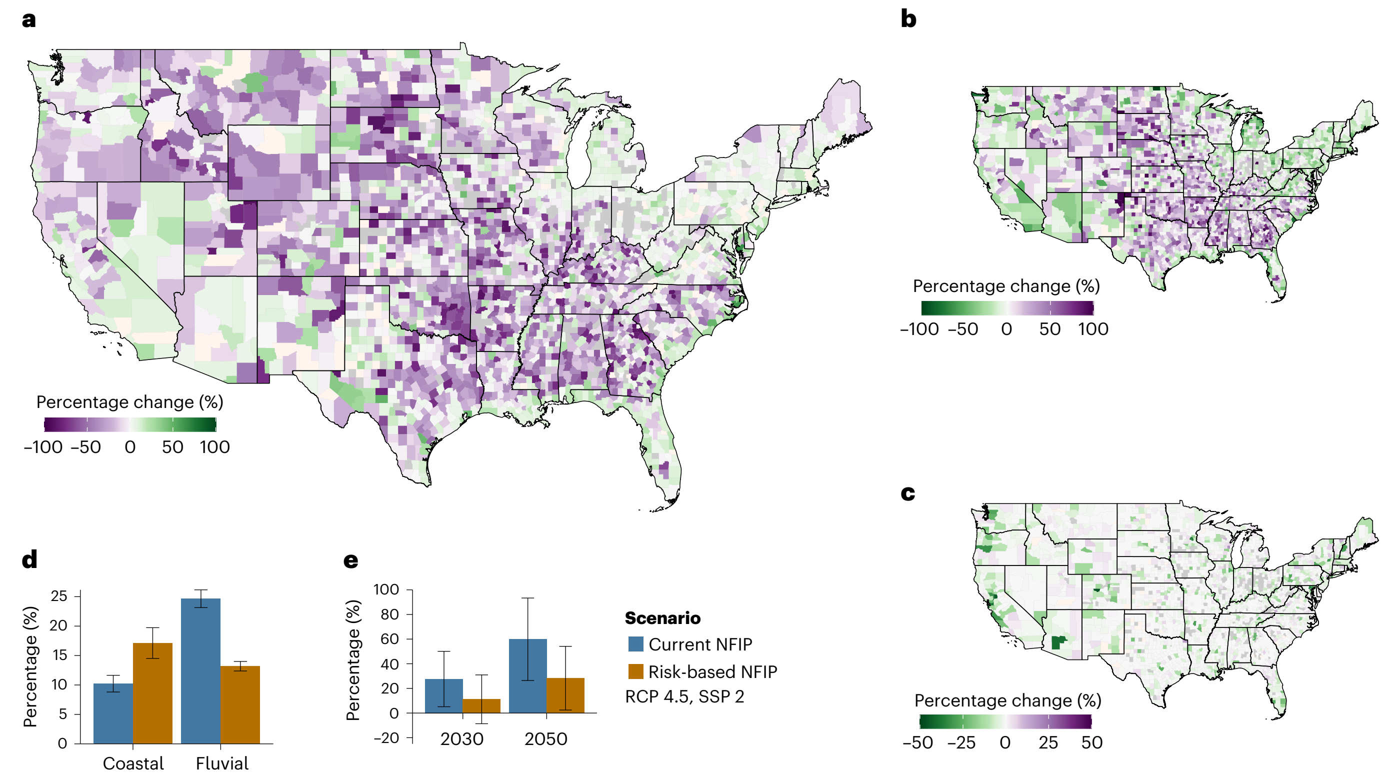

Fig. 1 | Effects of NFIP reform 2050 (RCP 4.5 + SSP 2). a–c, Effects of NFIP premiums to risk-based premiums in terms of market penetration (**a**), unaffordability (**b**) and risk (**c**) are visualized as the mean percentage change on a county level for 2050. **d**, Mean changes in penetration rates between coastal and fluvial risk areas. **e**, Mean insurer debt showing that debt might still increase despite risk-based premiums (although at a lower rate than under current conditions). For **d** and **e**, error bars indicate the standard deviation ($n = 250$ per scenario).

and are limited to assessing the current conditions. Recent debates on the restoration of aging infrastructure and studies on flood management suggest that complementary government-based investments in large-scale flood protection infrastructure (for example, dikes) are required to anticipate future climate risks and the increasing exposure of assets in flood-prone areas[2,3,9,10]. There is a lack of a comprehensive US-scale analysis of the NFIP that addresses how policy-holders will be impacted in the future by reforms, investments in governmental flood infrastructure and the ability of the NFIP to cope with climate change.

While the new reforms have been assessed in various studies[8], this study aims to complement the upcoming reforms by showcasing household behaviour patterns under different market structures and with different governmental adaptation investment efforts under climate change scenarios for fluvial and coastal flood risk. This is done by studying four indicators over time (2020–2050): insurance penetration rates, unaffordability of premiums and investment costs of risk-reduction measures, incentivization rate of building-scale disaster risk reduction (DRR) and the program's debt. The sensitivity of these indicators under future changes provides an indication of whether the programme will be financially healthy in the future. It also indicates the challenges that policy-holders may face. It should be noted that this paper does not aim to replicate or fully assess the Risk Rating 2.0 program as the NFIP Risk Rating 2.0 Delay Act of 2021 has delayed roll-out to 30 September 2022. We also show how households are incentivized to invest in DRR at the local level and highlight the importance of proactive governmental large-scale flood protection measures to complement the performance of the NFIP.

Conventional flood risk assessment methods are often ill-equipped to address flood management policy changes as they address neither interactions between key stakeholders nor household decision-making[11–13]. The spatial–temporal interplay between households, governments and insurance markets is key in gaining a comprehensive understanding of the NFIP and the effects of government policies. Recent literature demonstrates the applicability of agent-based models (ABMs) for topics related to flood risk and the effects of individual decision-making, such as evacuation[14], housing markets[15], climate change migration[16], community mitigation[17,18] and insurance markets[19].

This study is based on a new flood risk and agent-based modelling framework (Methods; Supplementary Information), which simulates dynamic decisions by homeowners regarding whether to implement DRR (for example, elevation or flood-proofing of buildings) and purchase flood insurance. We account for heterogeneous consumer behaviour and individual bounded rationality in risk perceptions[20,21]. Furthermore, governments can decide either proactively (using cost–benefit analysis based on yearly risk projections) or reactively (after a flood event) to invest in regional flood protection infrastructure. In turn, governmental proactive or reactive decision-making will influence the behaviour of homeowners. All the agents are provided with yearly risk projections from an underlying flood risk model, which is driven by climate change scenarios (RCP 4.5) and socio-economic projections (SSP 2) until 2050 (Supplementary Information). We apply this method to the conterminous US on a grid resolution of 30 arcsec.

Transition towards risk-based premiums

The effects of a transition from the current NFIP to risk-based premiums for 2050 is illustrated in Fig. 1, in line with the patterns found for the short-term effects in 2030 (Supplementary Fig. 2). Such transition leads to higher geographical heterogeneity of premium levels on a local scale. On a national scale, the model predicts that premiums will become relatively lower in coastal areas and higher in fluvial areas (although all premiums increase over time due to the effects of climate change

Table 1 | Total societal costs related to flood risk

Policy scenarios	A. Total flood risk (of which total residential risk) (US$billion)	B. Covered residential risk (US$billion)	C. Insurance premium expenses (US$billion)	D. Government flood protection investment costs (US$billion)	E. Household flood-proofing investment costs (US$billion)	F. Total societal costs A−B+C+D+E (US$billion)
Sc1: Baseline, current NFIP and reactive government	US$497 [34] (US$198) [15]	US$44 [3]	US$60 [2]	US$124 [57]	US$5.2 [4]	US$643 [74]
Sc2: Current NFIP+proactive government (relative to baseline)	−US$88 (−US$31)	−US$3.2	−US$2.5	+US$75	−US$1.2	−US$15
Sc3: Risk-based NFIP+reactive government (relative to baseline)	−US$8.9 (−US$9.0)	−US$19	−US$23	+US$0.0	+US$3.2	−US$10
Sc4: Risk-based NFIP+proactive government (relative to baseline)	−US$94 (−US$37)	−US$23	−US$28	+US$74	+US$1.0	−US$26

Results are based on RCP4.5 and SSP2 for the period 2020–2050. Cost categories are: F, cumulative cost from 2020 to 2050, which is the sum of uncovered total risk (covered residential risk (B) subtracted from total risk (A)); C, insurance premium expenses; D, governmental flood protection investment costs; and E, household flood-proofing investment costs. Values are expressed as present values (US$billion, 2020 at 4% discount rate) relative to the baseline scenario Sc1. Negative values denote a societal improvement and positive values indicate a cost for society compared with the baseline (note: numbers are rounded). Standard deviations are indicated in square brackets (n=250 per scenario).

compared to present day). These effects result in a decrease of insurance penetration rates in fluvial regions from 24.7% to 13.2% (partly due to an increase in unaffordability). This implies that (on average) the NFIP is currently underpricing these regions. Conversely, coastal regions display an increase from 10.2% to 17.1% in penetration rates due to more attractive premiums under risk-based insurance pricing for a share of households due to spatial variation in premiums. Still, a subset of policy-holders will experience a steep increase of their premium in these regions. Despite the lower penetration rates in fluvial regions, introducing risk-based premiums and offering premium discounts based on the actual reduction of risk achieved by flood-proofing buildings is expected to decrease the total average residential flood risk (coastal and fluvial) across the USA by about US$1 billion (−7.3%) by 2050. These results highlight the effectiveness of offering a premium discount to implement a variety of DRR types (wet and dry flood-proofing), including through retrofitting.

Our model demonstrates that unaffordability (Methods) is expected to decrease from 4.5 million households (23.8%) to 1 million households (5.6%) for the 18.8 million households at risk of floods nationwide in 2050 following a transition to risk-based premiums. However, the magnitude of the remaining unaffordability increases substantially to an average of US$2,000 per year per household. These findings indicate that although risk-based premiums are lower than current NFIP premiums for many households, moving towards risk-based premiums implies a sharp increase in premiums and unaffordability for a subgroup of households living in high-risk areas. Unaffordability issues can potentially be overcome by offering insurance vouchers and providing inexpensive accessible loans for financing DRR measures by low-income households currently living in high flood risk zones[7]. Alternatively, further incentivizing DRR by homeowners would make more people eligible for premium discounts. Relocation or managed retreat might also become necessary[2]. As seen in Fig. 1e, continuation of the program without anticipating climate change or socio-economic development will further increase the debt of the NFIP by ~60% (from US$20.5 billion to US$32.8 billion). Introducing risk-based premiums will significantly limit the rise in future debt but will not solve the problem entirely (debt will increase by 28% instead of 60%). An additional markup of premiums might be required to pay off current debt and make the program financially sound in the future.

Insurance schemes must be interlinked with flood adaptation

Our results show that additional large-scale flood adaptation investment complements a transition to risk-based premiums and household-level DRR measures[22]. Table 1 shows four policy scenarios: a baseline scenario (Sc1, current NFIP, reactive government) and three scenarios (Sc2, 3 and 4) with current and risk-based NFIP schemes and proactive or reactive government policies combinations. These are evaluated relative to the baseline Sc1 (see Methods for scenario descriptions and Supplementary Information for additional results). Table 1 displays the evaluation of these four scenarios for 2020–2050. It shows the present values of categories that address the total societal costs of flood risk and flood management. Total societal costs (F) are the expected cost of uncovered flood damage to properties and public assets (covered residential risk B subtracted from total flood risk A), insurance premium payments (C; costs of covered risk) and the costs of flood risk-reduction measures incurred by governments (D) and households (E). The results show that transitioning to risk-based premiums has a positive net present societal benefit of about US$10 billion for the period from 2020 to 2050, even when governments remain reactive towards investments in adaptation infrastructure. If the government acts proactively alongside risk-based premiums, the net present societal benefit increases to US$26 billion for the same period. Large-scale flood protection measures also have risk-reduction benefits over a longer lifespan than the 30-year period evaluated (2020–2050); hence, extending the analysis to the far future (for example, 2100) will favour proactive government policies even more. Accordingly, the government can reduce a large share of (future) flood risk by increasing flood protection through the installation of levees, the adoption of nature-based solutions or the implementation of other measures.

The community rating system (CRS) is a voluntary programme that incentivizes communities to actively engage in floodplain management activities that exceed the minimum programme requirement. The CRS could be used to further promote risk awareness and comprehensive floodplain management by communities and local governments in exchange for NFIP premium discounts to policy-holders in the community[22]. However, the full potential of the current implementation of the CRS is not yet used because only a small share of participating communities are actively reducing risk and the system does not consistently reward measures that consider future climate change risks[23]. As demonstrated by ref. [23], using the CRS to focus on regional flood protection goes hand-in-hand with the aforementioned NFIP reforms, since reducing flood risk through flood protection investments helps to keep insurance premiums affordable.

Risk-based premiums and flood adaptation infrastructure

Our analysis suggests that either moving towards risk-based premiums or proactively investing in large-scale flood protection yields significantly higher societal benefits. The highest societal benefits are achieved when adopting both strategies. Despite high upfront investment costs for large-scale adaptation of ~US$75 billion (compared to the baseline scenario), proactive investments are complementary to risk-based premiums. Together, they yield high average societal benefits ($26 billion, net present value for 2020–2050, Table 1). While the investment costs for large-scale adaptation seem high, the total societal benefits of US$26 billion with adaptation investments significantly surpasses the expected societal benefit of US$10 billion when only transitioning to risk-based premiums (Table 1). Furthermore, investing in flood protection infrastructure will reduce some of the equity issues (unaffordability) that arise when solely moving to risk-based premiums (columns C and E in Table 1). It will also reduce the risk to other governmental assets (for example, energy infrastructure and low-lying port areas). The remaining unaffordability issues for the subset of households with a major increase in insurance premiums could be addressed by offering insurance vouchers and providing low-interest accessible loans to further incentivize the implementation of DRR[7] or relocation[2].

The results of this study offer a timely contribution to both the Risk Rating 2.0 transition and the infrastructure bill. We show that there is significant synergy to be achieved by moving towards both a risk-based premium and a proactive strategy on large-scale adaptation. Our findings demonstrate that investing in large-scale adaptation does not reduce the effectiveness of risk-based premiums; in fact, it contributes to the reduction of unaffordability.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-022-01501-7.

References

1. Merz, B. et al. Causes, impacts and patterns of disastrous river floods. *Nat. Rev. Earth Environ.* **2**, 592–609 (2021).
2. Mills, E. Insurance in a climate of change. *Science* **309**, 1040–1044 (2005).
3. Ward, P. J. et al. A global framework for future costs and benefits of river-flood protection in urban areas. *Nat. Clim. Change* **7**, 642–646 (2017).
4. Winsemius, H. C. et al. Global drivers of future river flood risk. *Nat. Clim. Change* **6**, 381–385 (2016).
5. Tiggeloven, T. et al. Global-scale benefit–cost analysis of coastal flood adaptation to different flood risk drivers using structural measures. *Nat. Hazards Earth Syst. Sci.* **20**, 1025–1044 (2020).
6. Horn, D. P. & Webel, B. W. *Introduction to the National Food Insurance Program* (NFIP, 2019).
7. Michel-Kerjan, E. O. & Kunreuther, H. Redesigning flood insurance. *Science* **333**, 408–409 (2011).
8. *Risk Rating 2.0 Overview* (FEMA, 2019).
9. Mechler, R. & Schinko, T. Identifying the policy space for climate loss and damage. *Science* **354**, 290–292 (2016).
10. Di Baldassarre, G., Kooy, M., Kemerink, J. S. & Brandimarte, L. Towards understanding the dynamic behaviour of floodplains as human-water systems. *Hydrol. Earth Syst. Sci.* **17**, 3235–3244 (2013).
11. Di Baldassarre, G. et al. Debates—perspectives on socio-hydrology: capturing feedbacks between physical and social processes. *Water Resour. Res.* **51**, 4770–4781 (2015).
12. Di Baldassarre, G. et al. Socio-hydrology: conceptualising human-flood interactions. *Hydrol. Earth Syst. Sci.* **17**, 3295–3303 (2013).
13. Grames, J., Prskawetz, A., Grass, D., Viglione, A. & Blöschl, G. Modeling the interaction between flooding events and economic growth. *Ecol. Econ.* **129**, 193–209 (2016).
14. Dawson, R. J., Peppe, R. & Wang, M. An agent-based model for risk-based flood incident management. *Nat. Hazards* **59**, 167–189 (2011).
15. Filatova, T. Empirical agent-based land market: integrating adaptive economic behavior in urban land-use models. *Comput. Environ. Urban Syst.* **54**, 397–413 (2015).
16. Hassani-Mahmooei, B. & Parris, B. W. Climate change and internal migration patterns in Bangladesh: an agent-based model. *Environ. Dev. Econ.* **17**, 763–780 (2012).
17. Tonn, G. L. & Guikema, S. D. An agent-based model of evolving community flood risk. *Risk Anal.* **38**, 1258–1278 (2018).
18. Tonn, G. L., Guikema, S. & Zaitchik, B. Simulating behavioral influences on community flood risk under future climate scenarios. *Risk Anal.* **40**, 884–898 (2019).
19. Han, Y. & Peng, Z. R. The integration of local government, residents, and insurance in coastal adaptation: an agent-based modeling approach. *Comput. Environ. Urban Syst.* **76**, 69–79 (2019).
20. Haer, T., Botzen, W. J. W. & Aerts, J. C. J. H. Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modelling approach. *Environ. Res. Lett.* **14**, 044022 (2019).
21. Aerts, J. C. J. H. et al. Integrating human behaviour dynamics into flood disaster risk assessment. *Nat. Clim. Change* **8**, 193–199 (2018).
22. Sadiq, A. A., Tyler, J. & Noonan, D. S. A review of community flood risk management studies in the United States. *Int. J. Disaster Risk Reduct.* **41**, 101327 (2019).
23. Blessing, R., Brody, S. D. & Highfield, W. E. Valuing floodplain protection and avoidance in a coastal watershed. *Disasters* **43**, 906–925 (2019).

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Methods

Modelling framework

The core of the modelling framework was developed for the conterminous US, including the entire USA coastline and all main river basins. It simulated flood risk at a yearly time step with representative household adaptation at a resolution of 30″ × 30″ and government adaptation at the county level. Homeowners could invest in DRR measures (elevation or flood-proofing of buildings) or take out/cancel insurance and governments could invest in elevating dikes. Both these adaptations and the proposed NFIP reform policies were captured in four policy scenarios. The model was run 50 times for each of these policy scenarios while also assuming different climate scenarios and socio-economic scenarios. The framework builds upon earlier versions of DYNAMO[20,24]. New components are the flood insurance market module, the addressing of coastal flood risk in addition to fluvial flood risk and the nationwide application of the model. For the method description of the core model, please refer to ref. [20]. See also Extended Data Fig. 1 and Supplementary Information.

Flood risk model

The GLOFRIS flood risk model follows a commonly applied hazard–exposure–vulnerability model[25,26]. Coastal and fluvial inundation maps were combined with land use to simulate the (future) exposure of assets and their values in flood zones. Depth–damage curves were used to combine hazard and exposure data to simulate flood risk (expected annual damage, EAD, in US$ per yr) for each individual grid cell and county. Floods can stochastically occur every year in each county on the basis of their return period. See also Extended Data Fig. 1a and Supplementary Information.

Scenarios

Fluvial and coastal inundation maps are available for the current and future climate following the RCP 4.5 and RCP 8.5. The SSP scenarios[27–32] were used to represent the initial population numbers and to project population growth, income and economic growth for 2050. We applied the SSP 2 and SSP 5 scenarios as they matched well with RCP 4.5 and RCP 8.5, respectively. SSP 2 was a middle-of-the-road scenario, while SSP 5 was an energy-intensive and resource-intensive scenario. The former was used throughout the paper and the results of the SSP 5 scenario can be found in the Supplementary Information. See also Extended Data Fig. 1c.

Input data

Fluvial flood hazard. The GLOFRIS fluvial inundation maps are based on existing research[3,33]. In brief, daily time series of flood volumes were constructed using hydrological and hydrodynamic modelling at a 0.5° × 0.5° resolution. The GLOFRIS model was forced with EU-WATCH data for the period 1960–1999, representing historic conditions. For future conditions, the GLOFRIS model was forced with five global climate models (GCMs): HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M. Yearly maximum hydrological time series were extracted from the daily gridded flood volumes and a Gumbel distribution was fitted accordingly. The resulting Gumbel parameters were used to estimate (future) return periods for each grid cell: 5, 10, 25, 50, 100, 250, 500 and 1,000 yr. Finally, GLOFRIS distributed flood volumes to a digital elevation model to create high-resolution (30″ × 30″) inundation maps and their return periods[3,33]. See also Extended Data Fig. 1b.

Coastal flood hazard. For coastal inundation, as described in detail in ref. [5], the extreme sea levels are taken from the Global Tide and Surge Reanalysis (GTSR) dataset[34]. GTSR is a global dataset of daily sea levels (tide and storm surge) for 1979–2014, which is based on the Global Tide and Surge Model (GTSM). Within GTSM, tides are simulated separately using the Finite Element Solution (FES2012) hydrodynamic model[35]. Surges are simulated using metrological data from the ERA-Interim global atmospheric reanalysis[36]. The GTSR dataset is enhanced with historical tropical cyclone tracks over the period of 1979–2004, using the International Best Track Archive for Climate Stewardship archive, as GTSR is known for under-representing tropical cyclones. The extremes are subsequently calculated using a Gumbel fit of annual maxima using the maximum-likelihood method and validated in refs. [34,37].

To calculate coastal inundation, overland inundation from near-shore tide and surge levels were computed, after which the nearest GTSR location are projected at the coastline. A resistance factor is used to simulate the reduction of flooding land inwards, as tides and storm surges have a limited time span and therefore their flood peak and associated volume can only penetrate inland to a certain degree[5]. Coastal flood maps were made on a resolution of 30″ × 30″ for the same return periods as the fluvial flood maps: 5, 10, 25, 50, 100, 250, 500 and 1,000 yr, respectively[33]. For future conditions, mean sea level rise conditions were obtained from the RISES-AM project[38] and simulated as a range of probabilistic outcomes. For this paper, the 50th percentile was used. Future subsidence rates from the SUB_CR model and are included in the inundation model by adding the subsidence estimates to the MERIT digital terrain model[39]. In the areas where fluvial and coastal flood cells overlapped, we applied a simple method proposed by FEMA[40] and selected the highest inundation value.

For the continental scale and purpose of the study, the GLOFRIS model is sufficient. However, future research should focus on coupling ABMs with higher resolution flood hazard models (for example, ref. [41]) to increase the accuracy of risk simulations and to allow for improved analyses on the local scale.

Exposure. The GlobalLand30 (ref. [42]) database was used to estimate the exposure of urban assets. Urban grid cells within the GlobalLand30 dataset were set to 75% residential, 15% commercial and 10% industrial (with an assumed building density of 20% for residential and 30% for commercial or industrial)[5,43]. Future changes in residential surface area per cell were derived from the correlation between population growth and residential building surface growth[20]. The gross domestic product (GDP) growth from the SSPs was used to increase the value of properties over time.

Vulnerability. The vulnerability was represented by depth–damage curves (the relationship between inundation and the share of damage per land use type) and maximum damage values (the total amount of damage per land use type). The HAZUS Multi-Hazard model[44] of FEMA was used for the curves and the maximum damage values were taken from ref. [43] following existing methods[3,5]. The depth–damage curves were altered to simulate the effect of household DRR measures: dry flood-proofing (preventing flood water from entering a building) or elevation of new buildings[45]. Dry flood-proofing has a lifespan of 75 yr (ref. [46]), costs US$100 m^{-2} (Supplementary Table 5) and was implemented for water levels up to 1 m (FEMA[47]) reducing damage by 85%[48,49]. However, overtopping due to higher water levels resulted in full damage. For elevation, the vulnerability curve was shifted so that damage would only occur above 1 m of inundation.

Social vulnerability is represented by accounting for affordability in the adaptation choices of households. It is recommended for future research to also include other social vulnerability factors.

Current flood protection. Not all low-lying flood zones have the potential to be flooded due to the existing flood protection infrastructure (for example, dikes). The initial protection standards of levees in flood zones were based on the FLOPROS dataset[50]. Tiggeloven et al.[5] and others used an approach where protection levels were based on GDP but this resulted in very high protection levels for the USA (while observations suggested otherwise)[51,52]. Therefore, the coastal protection standards were set to 30-year exceedance levels[51,52], which can be changed by the governmental agents (equation (4)).

Policy scenarios

A total of four policy scenarios (Sc1–4) were simulated. These consisted of combinations of the following NFIP insurance and governmental policies:

- Sc1: current NFIP. This scenario simulated the current NFIP market structure as closely as possible. Observed premiums for 100-year flood zones and low-risk flood zones were used.
- Sc2: NFIP with risk-based premiums. Risk-based premiums were calculated by the flood risk model plus a loading factor of the current NFIP premium setting (estimated at 49.7%).
- Sc3: reactive government. Re-evaluation of protection standards of levees only occurred after a flood event in a county. Measures were implemented on the basis of a cost–benefit analysis using risk information from the model.
- Sc4: proactive government. Re-evaluation of protection standards occurred either every 6 years or after a flood event in the respective county. Measures were implemented on the basis of a cost–benefit analysis using risk information from the model.

Each policy scenario per RCP/SSP scenario was run for 50 repetitions for each RCP/SSP scenario per five GCMs, for a total of 250 repetitions each ($n = 250$).

Insurance market (ABM)

Premiums. Household decisions were based on yearly premiums (building and content coverage), which were simulated per grid cell of 30″ × 30″. See also Extended Data Fig. 1a. Start values of the premiums in Sc1 and Sc2 (current NFIP) were 2014 county averages for 100-year flood zones and low-risk flood zones[53]. State averages for premiums were used if county-level information was lacking. These 2014 premiums were adjusted to 2000 values at the start of the simulations. Next, these premiums were multiplied by the percentage change in yearly EAD simulated by GLOFRIS. It was assumed that yearly premiums changed before the yearly government decision on protection standards and the risk increase at that time step.

Premium discounts. For the scenarios with risk-based premiums (Sc3 and Sc4), unloaded premiums were initially calculated by the flood risk model. Subsequently, average NFIP loading factors (49.7%) were added[54,55]. Finally, a premium discount was applied using the CRS (Supplementary Information). Different discounts were applied for the 100-year and the low-risk flood zones (based on the ref. [53] dataset). Along with the CRS discounts, households that implemented DRR (elevation or flood-proofing) received a percentage premium discount that reflected the risk reduction obtained from implementing the DRR measure for the risk-based scenarios.

Mandatory insurance. Part of the NFIP is a mandatory purchase requirement for federally funded mortgages in a 100-year flood zone. Estimates show that, on average, 55% of the properties within a 100-year flood zone in participating communities are bound to the mandatory purchase requirement. However, research shows that an average of only 78% of those households comply[56]. We applied the 55% mandatory share for 100-year flood zones for participating communities and we benchmarked the compliance rate on affordability and the expenditure cap (that is, we assumed that if a households could not afford the policy premium, then they would not comply with the mandatory purchase requirement, resulting in an average compliance rate of 78%). After the initial model setup, households in non-participating communities can voluntarily adopt insurance over time but no mandatory requirement is enforced. It should be noted that this could lead to a higher insurance demand for inland communities that are non-participatory in the present.

Expenditure cap insurance. Following ref. [57] and ref. [58], we applied an expenditure cap definition for unaffordability. It was assumed that households could afford flood insurance if their annual premium was within the expenditure cap of their annual income, which was benchmarked at 7.5%. Income was distributed per county through a log-normal distribution based on mean and median income from the US Census Bureau 2010[59]. See also Supplementary Information.

Homeowner behaviour (ABM). Households that were not bound to the mandatory requirement had a yearly decision to take or cancel insurance. See also Extended Data Fig. 1a. First, (un)affordability was tested through the expenditure cap for insurance of 7.5%. Second, two strategies were compared following a subjective expected utility (EU)[20,60,61] model:

Strategy 1: *take insurance, accepting the deductible*

Strategy 2: *do not take or cancel insurance*

The strategy that yielded the highest EU was chosen. The subjective EU equation is as follows:

$$\mathrm{EU}_s = \int_{P_i}^{P_I} \beta P_i U\left(W_t - \gamma D_{i,t} \times \delta_s - C_{\mathrm{premium},t} - d_{\mathrm{premium},t}\right) dP \tag{1}$$

Equation (1) calculates EU_s for each strategy s. Each event i has a probability P_i of occurring with a factor β as perceived probabilities (see below). The total set of events I is the return periods of each flood event (with return periods of 5, 10, 25, 50, 100, 250, 500, 1,000 and 10,000 years, respectively) and the probability of no flood event. The EU_s is subsequently calculated as the approximation of the integral over I. Utility is calculated as a function of wealth W, uncovered damage D, factor γ as perceived damage (see below), premium C and a premium discount d (if applicable to the scenario). Damage D per event i for year t is calculated using the hazard–exposure–vulnerability model.

Risk aversion. A general utility function following constant relative risk aversion[62–64] was assumed. In line with common findings[62,63], households were assumed to be slightly risk-averse in which case $U(x) = \ln(x)$.

Deductibles. For strategy 1, homeowners had to pay a deductible δ of 10% of the incurred damages, while strategy 2 had full damages (no damage was covered, so $\delta_2 = 1$, $C = 0$ and $d = 0$).

Perception. Individuals act with bounded rationality in their decisions on buying flood insurance. This was represented by the perceived probabilities β and perceived damages γ. Both factors were benchmarked on the basis of empirical data by ref. [24] and simulated households overestimating their risk after a flood event while underestimating their risk after a period of no floods. Mathematically this is shown as:

$$\beta = 12.0639 \times \alpha_t^{3.71657} + 0.08233 \tag{2a}$$

$$\gamma = 0.442774 \times \alpha_t^{1.1671} + 0.802826 \tag{2b}$$

where $\alpha_t = 1$ if a flood occurs and $\alpha_t = \alpha_{t-1}/1.6$ if no flood occurs. This expression results in an increase during a flood event. In years with no storm events (the grid cell experiences no inundation), β and γ will subsequently decay to the inverse of the observed values in ~6 years after the storm event, in line with empirical evidence[65–67]. While homeowners were aware of increasing risk over time, it is assumed that they were not fully informed on flood risk due to their bounded rationality. Therefore, at the start of the simulations, each agent is assigned a different risk increase value picked from either a random-uniform distribution of the objective risk increase (simulated by the risk model) or no increase at all. It should be noted that individual risk perception is the main driver for changing behaviour but the decisions are also strongly influenced by the effectiveness of the adaptation measure and the income and wealth of the household, in line with coping appraisals[68]. For future work, it is recommended to assess the effects of including other drivers such as influences by neighbourhood behaviour.

Homeowner DRR and affordability. Affordability was tested before households could consider investing in individual adaptation measures (elevation for new properties and dry flood-proofing for existing properties). See also Supplementary Information. Elevation will prevent damages until the implementation height. Dry flood-proofing is preventing water from entering the property, which will lead to a decrease in damages up to 85% for implementation height[48,49]. However, inundation higher than the implementation height will cause overtopping and will result in full damages.

An expenditure cap for DRR was set to 2.5% (Supplementary Information) to define affordability (similar to the cap for insurance). Adjustments were made as these are long-term investments that have benefits over time but have high initial investment costs. Therefore, it was assumed that households could fund the investment through a personal loan with 15% interest over 5 years. The annual loan payment was used to test the affordability[24].

If the DRR options were affordable, each group (existing and new unprotected households) had the choice between two strategies:

Strategy 1: *implement disaster risk reducing measures*

Strategy 2: *do nothing*

This choice was determined on the basis of equation (3), which calculates the subjective discounted expected utility (DEU) as follows:

$$
\begin{aligned}
\mathrm{DEU}_s &= \int_{P_i}^{P_I} \beta P_i U(\mathrm{NPV}_s)\, dP = \int_{P_i}^{P_I} \beta P_i U\left(\sum_{t=1}^{T} \frac{W_t - \gamma D_{i,t,s}}{(1+r)^t} - \sum_{t=0}^{L} \frac{C_{\mathrm{annual},s}}{(1+r)^t}\right) dP \\
&= \int_{P_i}^{P_I} \beta P_i U\left(\sum_{t=1}^{T} \frac{W_t - \gamma D_{i,t,s}}{(1+r)^t} - \sum_{t=0}^{L} \frac{\frac{n * C_{0,s}}{1-(1+n)^L}}{(1+r)^t}\right) dP
\end{aligned}
\tag{3}
$$

The DEU model is calculated for strategy *s*. The variables *D, β, γ, W, P* and *i* and the general utility function *U(x)* are similar to those in equation (1). The net present value (NPV_s) is the sum of wealth W_t and the (reduced) damages $D_{i,t,s}$ over the lifespan of either measure *T*, discounted to the present value using discount rate *r*. The discount rate is the pure time preference of residents and is assumed to be 3%, following ref. [69]. The investment costs $C_{0,s}$ are US\$100 m^{-2} for dry flood-proofing and US\$45 m^{-2} for elevation (considering it only applied to new buildings). Following up the affordability metric, the investments are spread over 5 years through a personal loan with 15% interest (Supplementary Table 5), as an annual loan payment $C_{\mathrm{annual},s}$. For strategy 2 (without action), the NPV_s contains full perceived damages and no investment costs.

It should be noted that DRR investments and the uptake/cancellation of flood insurance are not mutually exclusive, nor does one lead to another. Each decision is simulated yearly and made decisions (such as investing in DRR) will impact future decisions during a model simulation.

Government large-scale adaptation. Governments had the ability to adapt by raising protection standards (5-, 10-, 25-, 50-, 100-, 250-, 500- and 1,000-year) each year per county. The initial fluvial protection standards were taken from the FLOPROS database[50]. A 30-year protection level was assumed for the coastal protection standards. (While some have aimed to determine coastal protection standards on the basis of GDP correlations, this is often not realistic for the USA as found by ref. [51] and others[52,70] (Supplementary Table 5).) Adaptation measures simulate increasing dike heights and all necessary additional adaptation measures (for example, beach nourishment and revetments), although some areas might be overestimated whereas other will be underestimated due to the scale of the model. During the initial modelling setup, these protection levels were matched with water levels to estimate an initial dike height. Protection standards could be increased by increasing dike heights for rivers and coasts for a county. The height increase was determined by using water levels associated with different return periods to reach the necessary protection level. If dikes were not upgraded over time, protection levels could decrease due to sea level rise and climate change effects.

The decision to increase dike heights was based on a cost–benefit analysis approach, whereby the present value of investment and maintenance costs was weighted against the present value of benefits from adaptation over time or mathematically:

$$
\begin{aligned}
\mathrm{NPV}_{\mathrm{PS}_i} &= \sum_{n=1}^{N} \sum_{t=1}^{L} \frac{B_{t,\mathrm{PS}_i,n} - C_{t,\mathrm{PS}_i,n}}{(1+r)^t} - C_{0,\mathrm{PS}_i,n} \\
&= \sum_{n=1}^{N} \sum_{t=1}^{L} \frac{(\mathrm{EADred}_{t,\mathrm{PS}_i,n} - \mathrm{EADred}_{t,\mathrm{PS}_{current},n}) - (C_{t,\mathrm{PS}_i,n} - C_{t,\mathrm{PS}_{current},n})}{(1+r)^t} - C_{0,\mathrm{PS}_i,n}
\end{aligned}
\tag{4}
$$

Here, NPV_{PS_i} is the net present value of investing in dike heights associated with a protection standard PS_i, calculated as the sum of each grid cell *n* for a specific county and over the lifespan of a dike *L* (assumed at 100 years)[71]. The benefits over time B_t are the difference between the reduction of EAD (EADred) between the new protection standard and the current protection standard $\mathrm{PS}_{\mathrm{current}}$. Similarly, the maintenance costs C_t are the difference between the new and current protection standard. Lastly, C_0 are the investment costs, the discount rate *r* (assumed at 4%) and time *t* in years. The maintenance costs are assumed at US\$0.1 × 10^6 per km and investment costs are assumed at US\$8 × 10^6 per length (km) per height (m)[48]. The protection standard with the highest NPV is chosen. If none of the protection standard has a positive NPV, nothing is done. For the reactive and proactive scenarios, we assume that when the government decides on adaptation, it makes decisions on the basis of perfect information on future developments of risk. As the proactive government takes adaptation decisions frequently and the reactive government very infrequently, we do capture an approximate upper- and lower-bound of government decision-making.

Agent interactions. Household and governmental agents interact through investing in either DRR measures or large-scale adaptation measures, respectively, reducing risk over time. Whenever a household reduces their flood risk by implementing DRR measures, this will directly influence their decision on insurance, through changes in the perceived probability of floods or the associated damage and a lower insurance premium for the risk-based insurance market scenarios. In addition, they reduce a (minor) share of regional flood risk, impacting the decisions by the regional government.

Similarly, if governments reduce risk by implementing regional-scale adaptation measures, then this will be reflected in a lower perceived probability and damage by households depending on the level of government protection. Via this mechanism, flood protection by the government thus influences household's decisions on adaptation investments and insurance uptake or cancellation.

Modelling robustness. We aimed to assess the sensitivity of proposed NFIP reforms under future conditions. To maximize the reliability of our model for this sensitivity analysis, we followed a three-step approach[72] (Supplementary Information): (1) benchmarking, (2) validation and (3) sensitivity analysis.

Benchmarking. Benchmarking of the GLOFRIS model has been extensively described by ref. [3,33]. With a hit rate of 70%, the global model performs well for the USA; however, it sometimes overestimates or underestimates inundations (Supplementary Information). This uncertainty is apparent when comparing the damage simulations to observed events (2000–2018): GLOFRIS underestimates three extreme hurricanes (Katrina, Sandy and Harvey) and overestimates other events (albeit to a lesser extent). We therefore applied a scaling factor (Supplementary Information) to better match the average observed damage. The underestimation of extremes can be explained by the dominant flooding processes during these events, which are not captured by our modelling setup (for example, levee breach; Supplementary Information) and also by the fact that tropical cyclones are not well-represented in the GTSR dataset[34].

Furthermore, the ABM model is upscaled from a benchmarked ABM for New York City using the same modelling decision rules and theory. However, the benchmarked parameters (risk aversion, protection standard, investment costs of dry flood-proofing, expenditure cap of dry flood-proofing investments, loan interest rate and loan duration) for New York City do not apply for the whole USA, which is why we applied standardized values of the parameters in the behavioural rules, as mentioned above. In addition, we benchmarked the parameter 'expenditure cap for insurance', by testing different values (2.5%, 5% and 7.5%) for this parameter and then ran the model 50 times for each of the parameter values. By comparing the number of policies per county as simulated by the model with the nationwide database (Supplementary Information), through a Spearman's Rho correlation test, the cap was set to 7.5% ($\rho = 0.679$; $P = 0.000$).

Validation. Modelling outputs for the years 2000–2018 were compared to FEMA data (Supplementary Information) using two indicators (insurance damage payouts and premium income). The model was run for 200 repetitions to account for uncertainty. Supplementary Table 6 shows a slight underestimation of mean yearly annual insurance damage payouts (US$2.8 billion versus US$3.0 billion) and a slight overestimation of premium income (US$1.7 billion versus US$1.3 billion) when comparing the model with the observed values, respectively. However, the standard deviation of the observed values was much higher, especially for the damages (0.9 versus 4.4 for the model and observed values). This last difference can be attributed to the underestimation of the damage by flood risk model for the three extreme hurricanes in the period 2000–2018.

Sensitivity analysis. The results from the validation provide confidence that, except for the three extreme events in the years 2000–2018, our modelled values of both damage payouts and premium income are close to their actual counterparts. However, to further test modelling uncertainty, a sensitivity analysis was conducted (Supplementary Tables 7–10), varying four key decision variables in the ABM:

(1) Reducing the expenditure cap for insurance of 7.5% decreases the share of policy-holders up to 15% and 42% for an expenditure cap of 5.0% and 2.5%, respectively. This is largely caused by an increase in household affordability. However, since other variables are only slightly influenced and the expenditure cap is benchmarked on the observed data, the used benchmark of 7.5% seems valid.
(2) Increasing the expenditure cap for DRR investments from 2.5% to 7.5% results in more households investing in DRR (up to 54% for an expenditure cap of 7.5%) and consequently reduces residential risk (up to 20%). However, the changes in results are relatively uniform between scenarios and do not affect the main conclusions of the paper.
(3) Increasing or decreasing the loan interest rates either decreases or increases the share of households that invest in DRR. However, this has a relatively low impact on results (with residential risk only changing by up to 4%).
(4) Varying the governmental investment costs by ±20% has only a minor impact on overall modelling results (for example, risk fluctuates by ±5% uniformly between scenarios).

Data availability
Land-cover data were obtained from GlobeLand[30,42]. Inundation data were obtained from the GLOFRIS cascade model[33]. Vulnerability curves were obtained from HAZUS-MH model[44]. Maximum damage values are available at ref. [43]. NFIP insurance data are available at ref. [55]. Income data were obtained from the US Census Bureau[59]. Protection standard database was obtained from FLOPROS[50]. NFIP Redacted Claims dataset is available from FEMA[73]. FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov. Socio-economic data were obtained from the International Institute for Applied Systems Analysis[74]. The generated data that support the finding of this study are available in figshare with the identifiers: https://doi.org/10.6084/m9.figshare.17049416.v1. There are no restrictions on data availability.

Code availability
The code for DYNAMO is available in Zenodo with the identifiers: https://doi.org/10.5281/zenodo.7025225. There are no restrictions on code availability.

References
24. de Ruig, L. T. et al. An agent-based model for evaluating reforms of the National Flood Insurance Program: a benchmarked model applied to Jamaica Bay, NYC. *Risk Anal.* https://doi.org/10.1111/risa.13905 (2022).
25. Kron, W. Flood risk = hazard • values • vulnerability. *Water Int.* **30**, 58–68 (2005).
26. de Moel, H., van Vliet, M. & Aerts, J. C. J. H. Evaluating the effect of flood damage-reducing measures: a case study of the unembanked area of Rotterdam, the Netherlands. *Reg. Environ Change* **14**, 895–908 (2014).
27. Riahi, K. et al. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob. Environ. Change* **42**, 153–168 (2017).
28. Samir, K. C. & Lutz, W. The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. *Glob. Environ. Change* **42**, 181–192 (2017).
29. Dellink, R., Chateau, J., Lanzi, E. & Magné, B. Long-term economic growth projections in the Shared Socioeconomic Pathways. *Glob. Environ. Change* **42**, 200–214 (2017).
30. Crespo Cuaresma, J. Income projections for climate change research: a framework based on human capital dynamics. *Glob. Environ. Change* **42**, 226–236 (2017).
31. Leimbach, M., Kriegler, E., Roming, N. & Schwanitz, J. Future growth patterns of world regions—a GDP scenario approach. *Glob. Environ. Change* **42**, 215–225 (2017).
32. Jiang, L. & O'Neill, B. C. Global urbanization projections for the Shared Socioeconomic Pathways. *Glob. Environ. Change* **42**, 193–199 (2017).
33. Ward, P. J. et al. *Aqueduct Floods Methodology* (WRI, 2020); www.wri.org/publication/aqueduct-floods-methodology
34. Muis, S., Verlaan, M., Winsemius, H. C., Aerts, J. C. J. H. & Ward, P. J. A global reanalysis of storm surges and extreme sea levels. *Nat. Commun.* **7**, 11969 (2016).
35. Carrère, L. & Lyard, F. Modeling the barotropic response of the global ocean to atmospheric wind and pressure forcing—comparisons with observations. *Geophys. Res. Lett.* https://doi.org/10.1029/2002GL016473 (2003).
36. Dee, D. P. et al. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.* **137**, 553–597 (2011).
37. Muis, S. et al. A comparison of two global datasets of extreme sea levels and resulting flood exposure. *Earths Future* **5**, 379–392 (2017).

38. Jevrejeva, S., Grinsted, A. & Moore, J. C. Upper limit for sea level projections by 2100. *Environ. Res. Lett.* **9**, 104008 (2014).
39. Kooi, H., Bakr, M., de Lange, G., den Haan, E. & Erkens, G. *User Guide to SUB-CR a MODFLOW Package for Land Subsidence and Aquifer System Compaction that Includes Creep* Deltares internal report 11202275-008 (Deltares, 2018).
40. *Guidance for Flood Risk Analysis and Mapping Combined Coastal and Riverine* (FEMA, 2015).
41. Bates, P. D. et al. Combined modeling of US fluvial, pluvial, and coastal flood hazard under current and future climates. *Water Resour. Res.* **57**, e2020WR028673 (2021).
42. Jun, C., Ban, Y. & Li, S. Open access to Earth land-cover map. *Nature* **514**, 434 (2014).
43. Huizinga, J., de Moel, H. & Szewczyk, W. *Global Flood Depth–Damage Functions: Methodology and the Database with Guidelines* (Publications Office of the European Union, 2017); https://doi.org/10.2760/16510
44. *Multi-Hazard Loss Estimation Methodology, Flood Model, HAZUS, Technical Manual* (FEMA, 2013).
45. de Ruig, L. T., Haer, T., de Moel, H., Botzen, W. J. W. & Aerts, J. C. J. H. A micro-scale cost–benefit analysis of building-level flood risk adaptation measures in Los Angeles. *Water Resour. Econ.* **32**, 100147 (2020).
46. Aerts, J. C. J. H. & Botzen, W. J. W. Flood-resilient waterfront development in New York City: bridging flood insurance, building codes, and flood zoning. *Ann. N. Y. Acad. Sci.* **1227**, 1–82 (2011).
47. *Homeowner's Guide to Retrofitting—Six Ways to Protect your Home from Flooding* (FEMA, 2014).
48. Aerts, J. C. J. H., Botzen, W. J. W., de Moel, H. & Bowman, M. Cost estimates for flood resilience and protection strategies in New York City. *Ann. N. Y. Acad. Sci.* **1294**, 1–104 (2013).
49. de Ruig, L. T. et al. An economic evaluation of adaptation pathways in coastal mega cities: an illustration for Los Angeles. *Sci. Total Environ.* **678**, 647–659 (2019).
50. Scussolini, P. et al. FLOPROS: an evolving global database of flood protection standards. *Nat. Hazards Earth Syst. Sci.* **16**, 1049–1061 (2016).
51. Hallegatte, S., Green, C., Nicholls, R. J. & Corfee-Morlot, J. Future flood losses in major coastal cities. *Nat. Clim. Change* **3**, 802–806 (2013).
52. Nicholls, R. & Cazenave, A. Sea-level rise and its impact on coastal zones. *Science* **328**, 1517–1520 (2010).
53. Czajkowski, J., Villarini, G., Montgomery, M., Michel-Kerjan, E. O. & Goska, R. Assessing current and future freshwater flood risk from North Atlantic tropical cyclones via insurance claims. *Sci. Rep.* **7**, 41609 (2017).
54. *Technical Documentation of NFIP Actuarial Assumptions and Methods* (FEMA, 2013).
55. *The National Flood Insurance Program: Financial Soundness and Affordability* (Congressional Budget Office, 2017).
56. Dixon, L. & Clancy, N. *The National Flood Insurance Program's Market Penetration Rate: Estimates and Policy Implications* (RAND Corporation, 2006); https://www.rand.org/pubs/technical_reports/TR300.html
57. Kousky, C. & Kunreuther, H. Addressing affordability in the National Flood Insurance Program. *J. Extreme Events* **1**, 1450001 (2014).
58. Hudson, P. A comparison of definitions of affordability for flood risk adaption measures: a case study of current and future risk-based flood insurance premiums in Europe. *Mitig. Adapt. Strateg. Glob. Change* **23**, 1019–1038 (2018).
59. *Income Data per County* (US Census Bureau, 2010); https://www2.census.gov/geo/tiger/TIGER_DP/2010ACS/
60. Von Neumann, J. & Morgenstern, O. *Theory of Games and Economic Behavior* (Princeton Univ. Press, 1947).
61. Hudson, P., Botzen, W. J. W. & Aerts, J. C. J. H. Flood insurance arrangements in the European Union for future flood risk under climate and socioeconomic change. *Glob. Environ. Change* **58**, 101966 (2019).
62. Harrison, G. W., List, J. A. & Towe, C. Naturally occurring preferences and exogenous laboratory experiments: a case study of risk aversion. *Econometrica* **75**, 433–458 (2007).
63. Bombardini, M. & Trebbi, F. Risk aversion and expected utility theory: an experiment with large and small stakes. *J. Eur. Econ. Assoc.* **10**, 1348–1399 (2012).
64. Wakker, P. P. in Wakker, P. P. (ed) *Prospect Theory for Risk and Ambiguity* Ch. 3 (Cambridge Univ. Press, 2008).
65. Kunreuther, H. Mitigating disaster losses through insurance. *J. Risk Uncertain.* **12**, 171–187 (1996).
66. Bin, O. & Landry, C. E. Changes in implicit flood risk premiums: empirical evidence from the housing market. *J. Environ. Econ. Manag.* **65**, 361–376 (2013).
67. Kunreuther, H., Sanderson, W. & Vetschera, R. A behavioral model of the adoption of protective activities. *J. Econ. Behav. Organ.* **6**, 1–15 (1985).
68. Bubeck, P., Botzen, W. J. W. & Aerts, J. C. J. H. A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk Anal.* **32**, 1481–1495 (2012).
69. Tol, R. S. J. The social cost of carbon. *Annu. Rev. Resour. Econ.* **3**, 419–443 (2011).
70. Nicholls, R. J. Coastal flooding and wetland loss in the 21st century: changes under the SRES climate and socio-economic scenarios. *Glob. Environ. Change* **14**, 69–86 (2004).
71. Aerts, J. C. J. H. A review of cost estimates for flood adaptation. *Water* **10**, 1646 (2018).
72. Cirillo, P. & Gallegati, M. The empirical validation of an agent-based model. *East Econ. J.* **38**, 525–547 (2012).
73. OpenFEMA Dataset: FIMA NFIP Redacted Claims (FEMA, accessed 23 June 2020); https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims
74. Keywan, R. et al. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Global Environmental Change 42, 153–168 (2017).

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Author contributions

The work was conceptualized by L.T.de R., T.H., W.J.W.B. and J.A. The methodology was developed by L.T.de R., T.H. and H.de M. Formal analysis was undertaken by L.T.de R. and T.H. Visualization was by L.T.de R. and H.de M. Supervision and funding acquisition were by J.A. The article was written by L.T.de R., H.de M., S.D.B., W.J.W.B., J.C. and J.C.J.H.A.

Competing interests

The authors declare no competing interests.

Additional information

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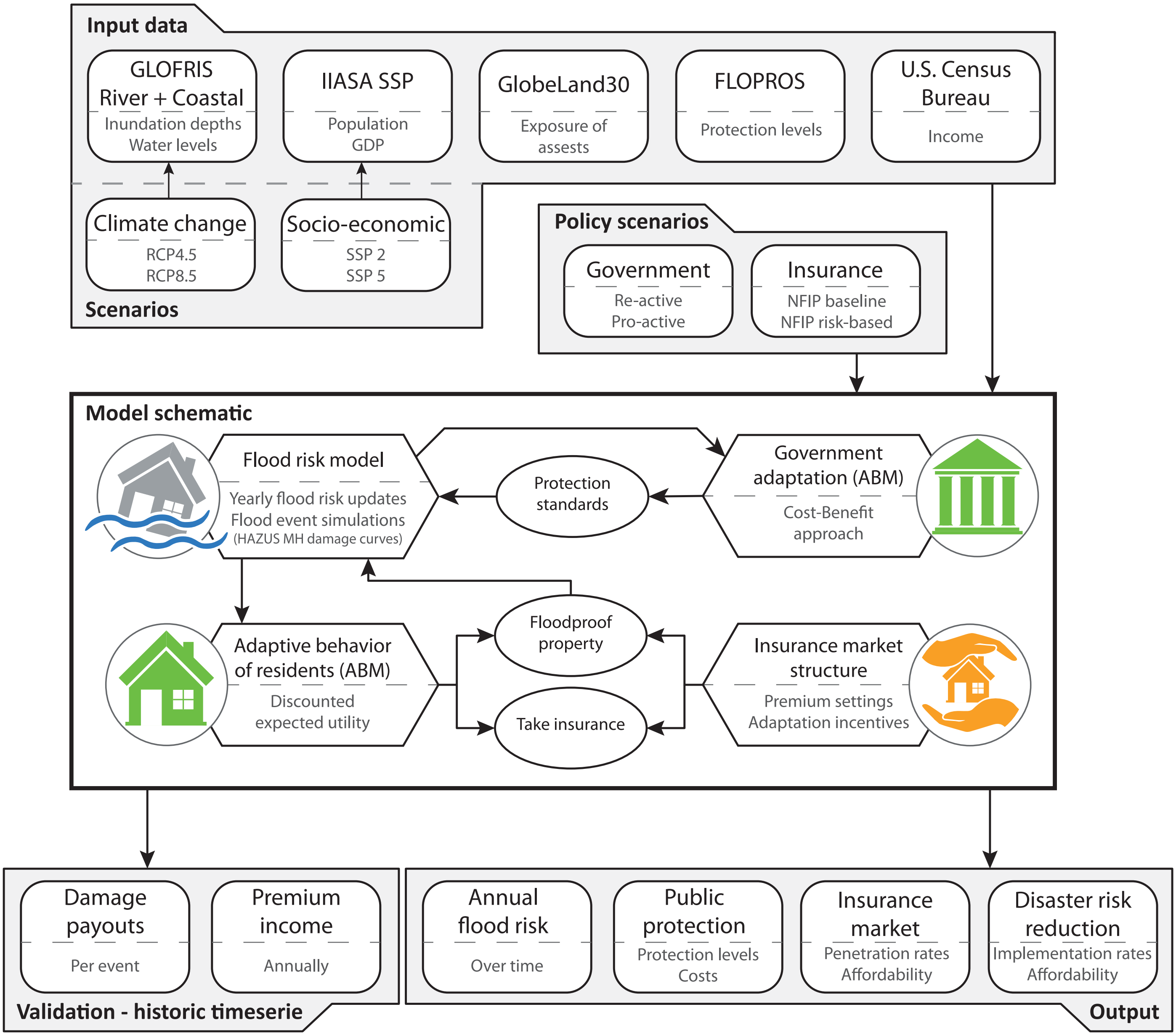

Extended Data Fig. 1 | A schematic overview of the primary modelling steps. A schematic overview of the primary modelling steps, showing the main buildings blocks of the DYNamic climate impact Adaptation Model (DYNAMO): **(a)** modelling schematic: a flood risk model and an agent-based model, **(b)** input data: flood maps, exposure data, flood protection data, income, **(c)** scenarios: socio-economic and climate change scenarios until 2050, **(d)** policy scenarios: governmental adaptation policies and NFIP market structures, **(e)** outputs: flood risk (EAD), insurance penetration rates, affordability, disaster risk reduction (DRR), and flood protection standards, (f) validation: damage and premium income. The framework builds upon earlier applications and version of DYNAMO by Haer et al.[21] for the EU and de Ruig et al.[28] for New York City.