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Not enough time to recover? Understanding the poverty effects of recurrent floods in the Philippines

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Abstract

Successful recoveries of households in the aftermath of extreme weather events are key to avoid long-term poverty implications. Yet, in frequently hit regions, there may not always be enough time for households to recover in-between recurrent events. There is a common narrative that the resulting incomplete recoveries aggravate adverse impacts, but there may also be counteracting mechanisms where a cluster of events leads to less destruction than a series of well-separated events because, after the first events, there are less assets left that can be destroyed by the subsequent events. To develop a systematic quantitative understanding for the interplay of the different mechanisms, we extend an agent-based household model to recurrent floods and study their welfare effects in the Philippines in dependence of household exposure and income. We find that incomplete recoveries increase cumulative consumption and well-being losses across the study period 2000-2018 by 50%. While low-income households suffer the highest well-being losses, lower-middle income households experience the largest relative increase in well-being (240%) and consumption losses (120%) due to incomplete recoveries. Our results show that the impacts of recurrent extreme weather events on households are not additive. In consequence, the well-being and consumption losses can be critically underestimated when concluding from the poverty implications of an individual event on the implications of recurrent events, as usually done in conventional disaster risk management. Thus, accounting for incomplete recoveries may allow to develop more effective risk management strategies and better prepare societies for an intensification of these events under global warming.

Introduction

There is increasing empirical evidence that extreme weather events such as floods can have adverse long-term impacts on households’ well-being through persistent losses of income but also adverse health impacts and food insecurities\textsuperscript{1,2}. Poor households are more exposed\textsuperscript{3–7}, more vulnerable\textsuperscript{4,6–8}, and take longer to recover than rich households\textsuperscript{9,10}. In consequence, extreme weather events can have severe poverty implications for poor households\textsuperscript{11,12}, especially in developing countries with limited means for adaptation and reconstruction efforts in the disaster aftermath\textsuperscript{5,13,14}. For instance, it has been shown empirically that households in the Philippines need years to recover from typhoon strikes. During the recovery phase they accumulate income losses summing up to over 90% of their total economic loss. Further, poor households are disproportionately affected since, in contrast to richer households, they cannot compensate for their income losses in the long-run\textsuperscript{15}.

Especially, in disaster-prone regions, households can experience a number of extreme weather (and associated natural hazards such as landslides after floods) events over their lifetime. Depending on a regions’ hazard profile, households may be affected by a series of events of the same category or by different event categories which may overlap spatially and temporally and simultaneously contribute to risk (compound events)\textsuperscript{16–18}. For our purposes, the risks of extreme weather events are most conveniently classified by their impact on households. When there is no measurable connection between extreme events, for instance because they are spatially or temporally so far apart that there
are no socioeconomic repercussions linking them, their impacts on households are additive. However, if events are connected for instance because households cannot recover between subsequent events, their impacts on households are non-additive and the compound impact can therefore be larger (or smaller) than the aggregate impact of the individual events \(^{19}\).

There is a rather extensive body of literature dealing with the impacts of multiple extreme weather events whose impacts are — in good approximation — additive \(^{20-22}\), for instance because there is sufficient time in-between subsequent events or they affect different areas of a country. However, much less work has been done on interconnected extreme weather events whose impacts are non-additive. There are some studies, where one extreme weather event changes the exposure or vulnerability to subsequent hazards \(^{19,23}\). For instance, the impact of extreme rainfall and flooding can be altered through a preceding drought \(^{24}\), e.g., due to disadvantageous drainage characteristics of dried out soil.

However, a comprehensive approach to quantify the distributional effects and poverty implications of households' incomplete recoveries between recurrent extreme weather events is still missing \(^{5,25-27}\). The intensification and frequency increase of extreme weather events \(^{28}\) may render incomplete recoveries more likely in the absence of adequate adaptation and resilience building measures. Therefore, it is important to better understand whether this intensification of extreme events would lead to a disproportionate increase of losses for households to allow for the development of farsighted coping national and local Adaptation Plans \(^{29,30}\) and climate-proof resilience building strategies \(^{27}\). Agent-based models appear to be well suited to assess the impacts of recurrent interconnected extreme weather events on households because they allow modelling differences in the exposure of households to these events with high granularity. Further, they can account for the heterogeneity of households with regard to their vulnerability and their means to recover from extremes and they allow us to explicitly model the interactions among households in the disaster aftermath \(^{31,32}\). Thus, differences in the speed and quality of the recovery between various groups of households differing e.g., by their income, social networks, access to financial support and working opportunities etc. can be modeled explicitly \(^{11,33}\). This in turn allows us to assess and compare the efficacy and limits of different post-disaster support and adaptation measures \(^{34}\).

In this work, we extend an agent-based model for the recovery dynamics of households in the aftermath of individual disasters \(^{11}\) to account for recurrent events. In each region, the model accounts for different groups of households, described by the FIES, which are distinguished by their income and the vulnerability of their physical assets (e.g., quality of housing) to floods (Tab. S1). We assume that households pay income taxes to the government which redistributes them through social transfers (given in the FIES), independently of flood exposure. Thus, in our model approach the total household income is the sum of their income from productive assets and social transfers (e.g. pensions). The share of income from social transfers is according to the FIES slightly higher for low-income households \(^{35}\), while the absolute amount of transfers increases with the income level (Fig. S2a). Flood shocks destroy the productive assets of the affected households (Methods), reducing the households’ ability to generate income to consume and invest into reconstruction of their assets. Households can also be affected indirectly by floods, as social transfers distributed by the government are reduced proportionally to its reduction in income tax revenues in the disaster aftermath (Methods). However, on a national level, the modeled reduction in the income of households that are only indirectly affected is comparatively low due to the relatively small number of directly flood affected households (Fig. S2a). We assume that in the aftermath of each flood shock, the affected households decide how to distribute their income among savings, consumption, and reconstruction investments by intertemporally maximizing their expected well-being over their foresight horizon of 15 years. Thereby, they try to keep up consumption for all members of the household above the subsistence line. The subsistence line denotes the consumption level at which households’ can satisfy their minimum basic needs \(^{36}\). In this work it is fixed throughout the simulations and encompasses basic needs in a narrow sense (e.g., needs of food, shelter, clothing, and medicine \(^{36}\)). We further assume that households cannot foresee future flood shocks nor
disaster-induced changes in social transfers and therefore do not account for them in the maximization of future well-being (Methods, Fig. 2a).

Asset damages and consumption losses are common disaster impact metrics. They have the advantage to be measurable in monetary terms and are therefore of great relevance for disaster insurance and fiscal stability measures in the disaster aftermath, respectively 4,37. However, these metrics cannot adequately describe welfare and poverty impacts of disasters for households 37,38. A marginal damage to households’ productive assets can lead to income losses forcing households to reduce consumption. Even if these consumption losses are small, they can be sufficient to push already poor households below the subsistence line where they struggle to satisfy their basic needs. Thus, a marginal loss in productive assets and consumption can result in a large reduction in households’ quality of life and well-being. In our modeling, this is captured by describing well-being as a concave function of consumption such that the same absolute consumption losses cause much larger well-being losses for poor than for rich households (Methods). Further, we use the recovery times of households as a metric to measure the poverty implications of recurrent extremes. We define the recovery time of a household as the time between the shock and the moment when the household has rebuilt at least 95% of its assets. Once vulnerable low income households are pushed below the subsistence line, their recovery becomes very difficult and slow and, in consequence, recurrent events can trap them in poverty 39–41. The slower the recovery of a household, the larger are the (monetized) well-being losses compared to the asset losses. This motivates the definition of socioeconomic resilience as the ratio of asset losses to (monetized) cumulative well-being losses to measure the capacity of households to cope with and recover from disasters.

Here, we find that national cumulative consumption and well-being losses are substantially increased through incomplete recovery between events. While low income households are most vulnerable to floods and suffer the highest well-being losses due to their comparably long recovery times, lower-middle income households perceive the largest additional relative well-being and consumption losses and drop in socioeconomic resilience due to incomplete recovery between recurrent events.

**Results**

In a factual scenario, we force the model by spatially explicit exposure to the reported time series of flood shocks. To this end, satellite-derived flood maps 42 are combined with population maps 43 where the estimated number of exposed people is rescaled to match the overall number of people exposed per event as reported by EM-Dat disaster database 44 (Tab. S2). As the survey data is not suitable to identify flood affected households, for each shock affected people are randomly attributed to households living in affected grid-cells (Methods). Thereby, we assure that on the regional level the household characteristics of the FIES (e.g., average household size, savings and household income per income group and region) are matched. We additionally distinguish a savings- and a no-savings scenario: in the savings scenario households can smooth consumption losses by their savings, while in the no-savings scenario households cannot employ their savings.

**National-level impacts of recurrent floods**

The Philippines are affected by floods in nearly every year of the study period 2000-2018. It is even likely that certain households experience even several flood shocks within one TC-prone rainy season in the summer months (Fig. 1a). This is why usually not all households affected by a flood event can recover before the next flood strikes (Fig. 3). In consequence, the aggregated damages to the households’ assets accumulates also on a national level over time leading to a simulated residual damages of about PHL 1 billion (or 0.02% of the households’ assets) at the end of the shock series. The sequence of events causes residual damages to the national stock of productive assets which takes decades to rebuild even in the absence of further shocks (blue shaded areas in Fig. 3).
To quantify the effects of incomplete recovery, we compare the factual scenario, where the same households can be affected multiple times, with two counterfactual scenarios (CFs): in the first CF scenario, the timing of the floods as well as the number of people affected by each flood remains unchanged but subsequent floods in the same area hit different households, so that each household is affected at most once (CF 1, Methods, Fig. 2b). In the second CF scenario, floods affect exactly the same households as in the factual scenario but the timespan between subsequent shocks has been extended such that there is always enough time for households to recover their assets (CF 2, Fig. 2c). The preservation of the timing of the observed shocks in CF1 allows us to single out the importance of households being hit more than once within the study period for the overall impact of incomplete recovery on the national level. Whereas CF 2 allows us to test for nonlinearities in the households’ response as a function of the number of consecutive shocks a household perceives.

Compared to the CF1 scenario, we find a stronger accumulation of the damage to the stock of productive assets over time in the factual scenario (cf. increasing spread between black and orange lines in Fig. 3a) resulting in an increase of residual damage by around 50% in 2018 and up to 100% a decade after the last event. The reason is that recovery times increase disproportionately when households fall below the subsistence line which becomes more likely when they perceive multiple shocks (Fig. S3). The slightly higher damage to the stock of productive assets observed for the first shocks in the CF1 can also be explained by the incomplete recovery of multiple flood affected households in-between events reducing the assets that can be destroyed by the floods in the factual scenario. However, after a few shocks this effect is overcompensated by the relatively slower recovery of households affected multiple times.

The damage to the stock of productive assets directly reduces the income of households and thus their ability to consume. This explains why consumption losses follow the dynamics of productive asset damages (Fig. 3b). Consumption losses are significantly higher than income losses as households not only have to reduce consumption due to their income losses but also at the expense of reconstruction investments in the disaster aftermath (Fig. S2a, Fig. 3b). Further, incomplete recovery of multiply-affected households increases residual consumption losses and well-being losses by around 25% and 40% in 2018 and around 90% and 60% after another decade without further shocks, respectively (Figs. 2b and c). Household savings moderately mitigate well-being losses for the first shocks of the sequence, but do not recover throughout the shock sequence (on a national level). This is why, in the factual scenario, the mitigating effect of savings on cumulative well-being losses saturates towards the end of the shock sequence. By contrast, in the CF1 scenario, household savings mitigate well-being losses throughout the flood sequence since each flood affects previously unaffected households.

**Distributional effects of recurrent floods**

The direct asset damages a household perceives from a flood shock depends upon the vulnerability of its assets which are derived from the building structure of its physical assets. According to the FIES survey (Tab. S2), building standards are positively correlated with household income. Thus, low income households are on average more vulnerable (Fig. S4). However, the relatively lower vulnerability of wealthier households’ assets is outweighed by the increase of (physical) assets with income (Fig. S6), resulting in an almost linear increase of absolute direct asset damages with income in both, the factual and the CF1 scenario (Fig. 4a). They are somewhat lower in the factual scenario because households are not always able to recover assets in-between shocks. There are three factors determining the recovery speed of a household: i) the relative damage depending on the asset vulnerability, ii) available construction investments, and iii) social transfers. Since social transfers are only indirectly affected by floods through reduced government tax revenues in the disaster aftermath, they are comparably stable and act as a social security mechanism for directly affected households that lost parts of their productive assets. Thus, households generating a higher share of income from social transfers recover more quickly. Since the share of income generated from social transfers declines only moderately with income (Fig. S2b), but asset vulnerability decreases (Fig. S4) and
available construction investments increase disproportionately with household income (Fig. 4a), the
time required for asset reconstruction (recovery time) declines with income (Fig. 4c). However, asset
vulnerability becomes a less important determinant for recovery times under incomplete recovery (Fig.
S5). On a regional level, the distribution of asset losses largely follows the pattern of exposed population, and the differences between the scenarios are most pronounced in regions experiencing many floods.

The dependence of well-being and consumption losses upon income is more complex than for direct
asset damages due to the interplay of two counteracting drivers: On the one hand, absolute direct
asset damages increases with income since richer parts of the population have more valuable assets
to lose (Fig. S6). This requires higher investments in reconstruction resulting in higher consumption
losses. On the other hand, richer households can afford to recover more quickly in the disaster
aftermath which decreases cumulative consumption losses. Which of these two drivers dominates
varies with income level leading to a non-monotonic dependence of consumption losses upon income.
For the factual scenario, consumption losses first increase with income for the first three deciles, then
decrease for deciles 4-9 due to faster recovery while consumption losses somewhat increase again for
the richest decile (Fig. 4b). By contrast, well-being losses monotonically decrease with income
across all income deciles, but relatively higher consumption losses result in a slower decay for the first
3 than for the other deciles (Fig. 4d). These differences between well-being and consumption losses
arise because even comparably small consumption losses can push poorer parts of the population
below the subsistence line leading to high well-being losses.

Comparing the factual scenario to the CF1 scenario reveals that incomplete recovery increases
well-being and consumption losses across all income deciles, with the exception of the poorest decile
for which consumption losses are somewhat larger in the counterfactual scenario (Fig. 4b and d).
Importantly, the effect of incomplete recovery is greatest for middle income households. The reason is
that these households recover from individual shocks nearly as quickly as rich households (see weak
dependence of the recovery time upon income for deciles 4 to 10 in the CF1 scenario in Fig. 4c).
However, hit by multiple subsequent shocks they are more likely to come close to — or even fall
below — the subsistence line than their richer counterpart. They then have to prioritize consumption
over reconstruction efforts which increases their recovery time disproportionately (Fig. 4c). By
contrast, households in the poorest three income deciles are often pushed under the subsistence line
even by a single shock, which critically slows down their recovery.

The regional pattern of well-being and consumption losses are largely determined by population
exposure, with the highest losses arising in Central Luzon. We find the largest effect of incomplete
recovery on well-being and consumption for lower-middle income regions such as Mimaropa, Western
Visayas, and Soccsksargen. In the poorest region, Bangsamoro, consumption losses even decrease
in the factual scenario compared to the CF1 scenario indicating that in this region recovery is
relatively slow, and consumption levels are low. After being hit once, the slow recovery of the affected
households leads to high and persistent consumption losses. In consequence, additional asset
damages from shocks only causes a comparably small additional consumption loss. This is why, in
Bangsamoro, overall consumption losses are higher in the CF 1 scenario where more households are
hit once compared to the factual scenario where fewer households are hit several times. For
well-being losses, the effect is reversed. Here the additional losses of fewer but multiply shocked
households outweighs the losses arising when more households are shocked once.

Since rich households can recover much faster than their poor counterparts, the decrease in
well-being losses with rising income overcompensates the moderate increase of absolute asset
damages resulting in a disproportional increase of socioeconomic resilience with income (Fig. 4e).
This steep increase of resilience with income is also reflected in the regional resilience patterns. Flood
prone but wealthy regions close to the capital region have substantially higher resilience than less
flood-affected but poorer regions in the south of the Philippines (Fig. 4e middle column). However, the
absolute reduction in resilience due to incomplete recovery is highest for wealthy, flood-prone
regions. A comparison of the factual with the CF1 scenario reveals that the socioeconomic resilience
is reduced by about 50% when households are not able to recover in between shocks, with a somewhat stronger decrease for lower-middle income groups (Fig. 4e right column).

**Frequently hit households suffer disproportional increase in well-being and resilience losses**

We next compare the factual with the CF2 scenario to assess the dependence of the household level impacts upon the number of flood events (Fig. 5 and Fig. S7). First we note that the direct asset damages a household of the highest income decile suffers from a single flood is higher than the total damages a household of the lowest income decile suffers from five consecutive floods. This disproportionality in losses mainly results from the unequal distribution of assets across income groups (Fig. S5) that is not compensated by the reduction of vulnerability with income (Fig. S4). Second, across all income groups, direct asset damages increases with the number of flood events (Fig. 5a, left column) but increases in damages with event number strongly depend upon the income of the affected households. The reason is that richest deciles can mostly recover in between events as shown by small differences between the factual scenario and CF 2. This results in a nearly linear increase of asset damages with event number (cf. bar height with vertical green lines in Fig. 5a, middle column). By contrast, the poorer the household the smaller is its ability to recover in between events which results in a sub-linear increase in absolute asset damages with event number.

In contrast to asset damage, consumption losses super-linearly increase with event number. In absolute terms, low-income households suffer the largest losses if affected by one or two flood events whereas the loss maximum shifts towards lower-middle income groups for higher event numbers (Fig. 5b, left column). The underlying reason is that the recovery of the poorest households living close to — or even below — the subsistence line is slow irrespective of the number of floods affecting them. By contrast, lower-middle income households have sufficient means to recover relatively quickly from one or two flood events but are pushed towards the slow recovery regime in the vicinity of the subsistence line if affected by more than two floods. Upper-middle and high-income groups usually retain enough means for a comparably swift recovery irrespective of the number of floods affecting them. Thus, in relative terms lower-middle income households suffer the largest consumption losses due to incomplete recovery if affected by more than two floods and this relative loss increase becomes more pronounced with event number (Fig. 5b). For instance, for households of decile 4, the consumption losses of three consecutive events are larger than of seven independent events (Fig. 5b, middle column). The comparably high consumption losses of the wealthiest decile of households with regard to households in deciles 5-9 (upper-middle to wealthy) across all event numbers reflects the disproportional high consumption share of the former (Fig. S1).

The dependence of well-being losses upon event number is qualitatively similar to the dependence of consumption losses (Fig. 5c, left column). Notable differences are that absolute well-being losses are always largest for the poorest decile while, for the richest decile, they remain comparably small irrespective of the event number reflecting the concave dependence of well-being upon consumption. Quantitatively, distributional effects are more pronounced for well-being than for consumption losses. For instance, households of the poorest three deciles experience higher well-being losses from a single flood event than the richest three deciles from five consecutive events (Fig. 5c, left column). Similarly to consumption losses, the effect of incomplete recovery is strongest for lower middle income households. For instance, if affected by five consecutive events, the well-being losses for households of these income groups are higher than the losses they would suffer from 18 independent events (Fig. 5c, middle column).

**Discussion**

There is growing concern that the increasing number of extreme events expected under climate change may push people into poverty traps and that recurrent extreme weather events must no longer be considered as a sequence of rare, independent events ignoring overlapping recovery dynamics.
While so far there only is anecdotal evidence for the detrimental effects of incomplete recovery\textsuperscript{5,25}, we introduce a model and simulation set-up to formalize the test of this hypothesis and quantify the effect of incomplete recovery of households between recurrent flood shocks. To this end, we combine a newly available satellite-based dataset for flood shocks in the Philippines with an agent-based model for the recovery dynamics of households that we extend to account for potential non-additive effects in the households’ response dynamics to recurrent floods.

This approach allows us to go beyond asset damages, the conventional metric of disasters, to assess consumption and welfare losses. This is important for two reasons: first, the extension allows for risk managers to assess and manage disparate welfare costs of extreme weather events, especially to the benefit of low-income households\textsuperscript{3,5,8}. We find that discounted consumption losses accumulate over the simulation period to more than twice the cumulative asset damages (+210\%). These findings are well in line with purely empirical works finding that most losses of typhoons to households in the Philippines arise from income losses in the disaster aftermath and not from the direct impact of the storms on households’ assets through strong winds, rainfall and storm surge\textsuperscript{15}. Further, the poorest are most vulnerable to floods and suffer the highest well-being losses among all income groups. Living already close to the subsistence line, they struggle to fulfill their basic needs such as sufficient access to clean water, education, and healthcare even in times without disasters. This leaves them with little means to recover from flood shocks\textsuperscript{45} resulting in a slow recovery and an elevated risk of being trapped in poverty\textsuperscript{8,39} by subsequent flood events. We find incomplete recovery to substantially increase cumulative consumption by 25\% and well-being losses by 40\%, respectively, over the study period of 18 years. Importantly, lower-middle income households perceive the largest additional relative well-being losses (+240\%) and consumption losses (+120\%) and drops in socioeconomic resilience due to incomplete recovery in the historical period. While these households have enough financial means to recover relatively quickly from an individual flood, recurrent floods can push them close to — or even below — the subsistence line, critically slowing down their recovery and driving up well-being and consumption losses.

Our modeling approach highlights that many of these dynamics are missed when floods are considered as rare, independent events which without adaptation and coping strategies lead to a critical underestimation of losses and a non-optimal allocation of reconstruction and resilience-building efforts that do not appropriately account for the differential needs of the various income groups of households. Regarding short-term interventions and support, our study highlights that in order to reduce the critical well-being losses of the poorest, it is not effective to reduce consumption losses uniformly across all income groups. Instead, consumption losses should be reduced with a focus on efficient well-being improvements\textsuperscript{6}. The finding that recurrent floods can push even lower-middle income households below the subsistence line suggests that support measures should be tailored towards the post-disaster needs of these groups (in addition to the poorest part of the population). Putting these insights together, welfare and consumption-informed risk management strategies awareness leads to more and cheaper opportunities for risk mitigation and recovery. More opportunities, because we are able to assess the welfare and economic benefits of investments and interventions that do not affect asset damages. Cheaper opportunities, because distributional awareness informs more targeted and efficient investments.

The households’ resilience model comprises several simplifying assumptions and parameter uncertainties (Table 1). First, we assume a closed national economy without financial flows from and to the Philippines. This may be a substantial limitation since post-disaster support as international aid and remittances play an important role during the recovery process\textsuperscript{11,46,47}. Related to this, we do not model additional adaptation efforts that likely have led to a reduction of households’ flood vulnerability during the study period\textsuperscript{48,49}. We here decided to nevertheless focus on an “alone-out-in-the-dark” scenario where neither international post-disaster support nor additional adaptation efforts are taken into account in order to reduce the number of confounding drivers. This allows us to gain a better understanding of the main mechanisms through which interconnected floods affect the households’ recovery dynamics and thus household consumption and well-being. Second, we do not i) consider a
labor market in the model, and ii) explicitly model critical infrastructure and other public physical capital. Both are potentially important channels through which floods impact on households recovery and the economy in general. Resolving these channels in future versions of the model would also allow assessing adaptation options such as the hardening of critical infrastructure explicitly. Further, we base the modeling on the socio-economic situation of the year 2015 and neglect population growth, within-country migration, and potential income-specific exposure changes over the study period 2000—2018. Therefore, we may overestimate the number of events individual households experience, as some households may move to less exposed areas. In consequence, the effect of incomplete recovery on a national level may be overestimated. On the other hand, the reported number and extensions of floods is likely to be underestimated in the GFD database, due to missing events in the reporting and cloud cover that may obscure parts of the flooded areas.

Here, we focus on the contribution of incomplete recoveries to the distributional and poverty effects of recurrent floods in the Philippines. However, since the channels through which extreme events may be similar for other major event categories, our findings are likely transferable to other countries affected by extremes of different or multiple categories (multi-hazards). Importantly, our results underline the inadequacy of development policies targeted on “easy wins” to reach adaptation and development goals, for instance by lifting poor households just above the poverty line. Being not always able to recover between floods, these households could be pushed again below the poverty line by recurrent floods. Thus, we may conclude that to reduce chronic poverty, adaptation strategies are needed that foster the recovery speed of households. Further, our insights on additional well-being losses due to incomplete recoveries could be helpful for countries where interconnected extreme weather events have played a minor role in the past but may become important with the intensification of these events under global warming. The costs of inaction or even maladaptation could be especially high in these countries since the intensification of extreme weather events may aggravate the problem of incomplete recovery, especially for low and lower-middle income populations in the absence of adequate resilience building efforts. Thus our study may critically inform the development and implementation of farsighted National Adaptation Plans, and national and international disaster risk reduction strategies.

Materials and Methods

Flood data

To generate a realistic sequence of flood affected areas for the Philippines, we use satellite images providing spatially explicit flood (8” ~ 222m) maps from the Global Flood Database (GFD). It lists 44 flood events in the time period 2000-2018 and comprises information on displaced people. In general, the database groups flood events into one of the following categories: i) Heavy rain; ii) Tropical Storm, Surge; iii) Snowmelt, Ice, Rain; iv) Dam. In the Philippines all events are grouped into either category i or ii. Here, we include all the flood events given in the database regardless of the event type.

Socio-economic data

Household characteristics (total income, income from social transfers, building standards, location (regions-ADM1) are extracted from the Family income and Expenditure Survey (FIES). The FIES provides household census data on income, consumption, and living conditions representative for all households living in the Philippines. As not all households can be sampled, questioned households receive a weight \( w_i \) indicating how many households it represents. The survey data is representative on the regional level, so it is not possible to extract the exact coordinates of a household. The national population distribution on a 30” (~1km) resolution of the Philippines in 2015 is derived from the gridded-population-of-the-world (GPW v4) dataset. For model calibration we use flood affected people from The International Disaster Database (EM-DAT) for each event.
The agent-based household resilience model

We present an extension of the household resilience model of ref. 11 that allows simulating the households’ response dynamics to recurrent extreme weather events (cf. Fig. 1 and Fig. 2). The model describes an economy consisting of heterogeneous households that differ, among other things, by their income, vulnerability, and exposure to extreme weather events, and a government that collects income taxes and distributes the tax revenues as social transfers to the households.

The total income of a household \( i_h(t) \) at each point in time is composed of income from its stock of productive (physical) assets (capital stock) \( i^{\text{eff}}_h(t) = \pi k^{\text{eff}}_h(t) \) and its income from social transfers \( i^{sp}_h(t) \),

\[
i_h(t) = i^{sp}_h(t) + (1 - \delta^{\text{tax}}_{sp}) i^{\text{eff}}_h,
\]

where we have introduced the income tax \( \delta^{\text{tax}}_{sp} \) and the productivity of capital \( \pi \). The households’ consumption \( c_h(t) \) varies with its income \( i_h(t) \), disaster response, and precautionary savings \( s_h(t) \) as detailed in Secs. Economic equilibrium and Recovery dynamics. The utility that a household gains from its consumption is described by a standard constant relative risk aversion (CRRA) utility function

\[
u_h(t) = c_h(t)^{1-\eta} - \frac{1}{1-\eta},
\]

where the elasticity of the marginal utility of consumption \( \eta \), expresses that a unit change in utility affects the well-being of poorer households more than of richer households. It represents both the risk aversion and the aversion to inequality in a society and is linked to preferences and values.

The households’ cumulative well-being is then the time integral of the utility function over the simulation time \( t_{sim} \)

\[
W_h = \int_{0}^{t_{sim}} u(t) dt
\]

Government income consists of the taxes collected from all households

\[
i_g(t) = \sum_{h=0}^{N} w_h i_h(t) \delta^{\text{tax}}_{sp}
\]

where \( N \) denotes the number of modeled households and \( w_h \) is the household weight measuring the part of the Philippines’ population that is represented by the household agent in the model.

Government expenditure is given by the sum of the social transfers \( i^{sp}_h \) disbursed to the households

\[
C_{sp}(t) = \sum_{h=0}^{N} w_h i^{sp}_h(t)
\]

. We assume that the government’s fiscal balance remains always in equilibrium, i.e., at each time-step government income equals government expenditure.

Economic equilibrium

In the absence of shocks, the economy is in equilibrium described by a steady state. In the following, we denote the steady state values of variables by a subscript \( * \). The steady state values of total household income \( i^*_h \) and income from social transfers \( i^{sp,*}_h \) are taken from the FIES survey.
The steady state value of the social transfers then reads
\[ C_{sp}^* = \sum_{h=0}^{N} w_h i_{h}^{sp,*}. \]
Since the government’s budget is balanced, the income tax revenues must equal the costs from social transfers allowing to derive the income tax rate as,
\[ \delta_{sp}^{tax} = \frac{C_{sp}^*}{\sum_{h=0}^{N} w_h i_{h}^{eff,*}}. \quad \text{Eq. 4} \]

The steady state value of each household’s asset stock can then be estimated from its income \( i_{h}^* \) as,
\[ k_{h}^{eff,*} = \frac{i_{h}^* - i_{h}^{sp,*}}{(1 - \delta_{sp}^{tax})\pi}. \quad \text{Eq. 5} \]

Further, the steady state value of the national stock of physical assets is given as
\[ K^* = \sum_{h=0}^{N} w_h k_{h}^{eff,*}. \]

In the steady state, households consume all of their income \( c_{h}^* = i_{h}^* \) and keep a constant stock of precautionary savings \( s_{h}^* \). The FIES provides an estimation of the total household expenditure \( c_{h}^{FIES} \) that allows to determine the annual balance of income and expenditure of each household and its annual surplus. We assume that in the steady state every household keeps one year’s surplus as precautionary savings \( s_{h}^* = i_{h}^* - c_{h}^{FIES} \), but does not accumulate further savings.

**Recovery dynamics in the aftermath of floods**

In the aftermath of a flood, each directly affected household decides upon its optimal recovery rate \( \lambda_{h} \) by intertemporally maximizing its expected future well-being (Eq. 3) from consumption \( c(t) \) over their planning horizon \( T_p \) with the future discount rate \( \rho \),
\[ \max_{c(t)_{t'=t_{shock}+T_p}} \int_{t_{shock}}^{t_{shock}+T_p} W_h u(c(t))e^{-\rho(t-t_{shock})}dt \quad \text{subject to } c(t) \geq c_{sub} \text{ for } t \in [t_{shock}, t_{shock} + T_p]. \quad \text{Eq. 6} \]

Thereby the household tries to avoid falling below the subsistence level of consumption \( c_{sub} \) at any point in time \( t' \in [t_{shock}, T_p] \), and the consumption can be written as \( c(t) = c_{h}^*(t) - \Delta c_{h}(t) \). The total consumption losses \( \Delta c_{h}(t) \) of a household in the recovery phase (at time \( t \geq t_{shock} \)) equal the sum of its income losses \( \Delta i_{h}(t) \) plus its spendings on asset recovery \( \Delta c_{h}^{reco}(t) \) minus available precautionary savings \( s_{h}(t) \),
\[ \Delta c_{h}(t) = \Delta i_{h}(t) + \Delta c_{h}^{reco}(t) - s_{h}(t). \quad \text{Eq. 7} \]

In the following, we derive expressions for the contributions \( \Delta i_{h}(t) \) and \( \Delta c_{h}^{reco} \). The spending of precautionary savings allows to smooth peak consumption losses. As the spending rate depends on the recovery pathway we discuss this in a specific section (cf. Sec. Spending of precautionary savings).
Consumption reduction due to recovery efforts

When a flood strikes at time $t_{\text{shock}}$, it directly affects a certain fraction of the households in the flood-affected area (cf. Model calibration).

Which share $\Delta k_h^{\text{eff}}$ of its stock of physical assets $k_h^{\text{eff}}(t)$ a directly affected household loses depends on the vulnerability $\nu_h^* \in (0, 1)$ of its assets,

$$\Delta k_h^{\text{eff}}(t) = \nu_h^* k_h^{\text{eff}}(t). \tag{8}$$

This asset vulnerability varies among households and is directly estimated from the building structure given in the FIES survey as discussed in Sec. Model Calibration.

Each directly affected household is assumed to rebuild its asset stock exponentially,

$$\Delta k_h^{\text{eff}}(t) = \Delta k_h^{\text{eff}}(t_{\text{shock}}) e^{-\lambda_h(t-t_{\text{shock}})}. \tag{9}$$

Thereby, the household has to choose the rate of reconstruction $\lambda_h$ carefully since to finance the reconstruction efforts, it has to reduce its consumption proportionally to $\lambda_h$ and $\Delta k_h^{\text{eff}}$.

$$\Delta c_h^{\text{reco}}(t) = -\frac{d}{dt}(\Delta k_h^{\text{eff}}(t)) = \lambda_h \Delta k_h^{\text{eff}}(t). \tag{10}$$

Income losses in recovery phase

In general, the flood affects the income of a household through two impact channels. First, directly affected households perceive income losses that are proportional to their losses $\Delta k_h^{\text{eff}}(t)$ in productive assets (cf. Fig. 2a). Second, all households that receive social transfers are affected by reductions of social spendings of the government in the disaster aftermaths. Through the second impact channel, floods also affect households which are not directly affected by the disaster. Since we assume that the government does not take up additional debt in the disaster aftermath, the reduction in social transfers is directly proportional to the national losses in productive assets relative to the steady state value of the national stock of productive assets $\bar{K}^*$. Combining both channels allows to express the income losses of a household as,

$$\Delta i_h(t) = \max[0, (1 - \delta_{\text{sp}}^{\text{tax}})\pi \Delta k_h^{\text{eff}}(t) + \frac{L(t)}{K^*}i_h^{\text{sp}}]. \tag{11}$$

Determination of the optimal reconstruction rate

We assume that households do not account for disaster-induced changes in social transfers and further neglect their precautionary savings when determining the optimal reconstruction rate of the capital stock $\lambda_h$ by maximizing their expected well-being $W_h$ over their foresight horizon $T_F$ in the disaster aftermath. For the well-being maximization, we therefore set $\lambda_{\text{sp}}^{\text{tax}} = \pi = s_h = 0$. Inserting Eqs.7-11 into the general form of intertemporal well-being (Eq. 6), then allows us to write $W_h$ as,
Here, we have introduced the vulnerability $\nu_h$ that represents the ratio of the damaged physical asset stock directly after the shock to its steady state value, $\nu_h = \frac{\nu_h^{\text{eff}, \ast}}{k_h^{\text{eff}, \ast}}$. The necessary condition (Euler equation) for the (unconstrained) well-being maximization then reads, 

$$\frac{\partial W}{\partial \lambda} = 0,$$

Eq. 12

$$\Leftrightarrow 0 = \int_0^{T_p} \left[ \pi - (\pi + \lambda_h^{\text{eff}}) \nu_h e^{-\lambda_h^{\text{eff}}(t-T_p)} \right] - \eta \left( (\pi + \lambda_h^{\text{eff}}) - 1 \right) e^{-(\rho+\lambda_h^{\text{eff}})t} dt.$$

The integral cannot be solved analytically, we determine the optimal $\lambda_h^{\text{eff}}$ numerically. We label this recovery process where the constraint that consumption must not fall below its subsistence level is not binding as recovery type 1 and the resulting recovery rate as $\lambda_h^{\text{eff}}_1$ (cf. Fig. S3a). Beneath the type 1 recovery we consider three more recovery types that arise when the consumption constraint is binding and the household would (temporally) fall below the subsistence line when determining its asset reconstruction rate from Eq. 12. To avoid falling below the subsistence line, some households have to recover at a lower pace but can always keep their consumption above subsistence level during the recovery phase (type 2 recovery),

$$i_h^* - \Delta i_h(t) - \lambda_h^{\text{eff}} \Delta k_h^{\text{eff}} < c_{sub} \text{ and } i_h^* - \Delta i_h(t) > c_{sub}.$$

We assume that type 2 households determine their recovery spending in every time step until exponential recovery with $\lambda_h^{\text{eff}}_2$ is possible in $t_{exp}$. These households reduce in each timestep, in which they cannot afford reconstruction with $\lambda_h^{\text{eff}}_1$, its consumption to the subsistence level less the constant recovery spending of households in subsistence $R_{sub}$ (cf. Sec. Model Calibration), and uses its remaining post-disaster income plus the constant recovery average savings rate of households in subsistence $R_{sub}$ (cf. Sec. Model calibration) to reconstruct (Fig. S3b),

$$\lambda_h^{\text{eff}}_2(t) = i_h^* - \Delta i_h(t) - c_{sub} + R_{sub},$$

Eq. 14

Thus, the recovery of its asset stock can be written as,

$$\Delta k_h^{\text{eff}}(t) = \begin{cases} \Delta k_h^{\text{eff},<}(t) - \lambda_h^{\text{eff}}_2(t) & \text{if } i_h^* - \Delta i_h(t) - \lambda_h^{\text{eff}}_1 \Delta k_h^{\text{eff}} < c_{sub}, \\ \Delta k_h^{\text{eff}}(t_{exp}) e^{\lambda_h^{\text{eff}}_1(t-t_{exp})} & \text{else}, \end{cases}$$

where $\Delta k_h^{\text{eff},<}(t)$ denotes the losses to the capital stock at the beginning of time step $t$.

A household that falls under subsistence line due to the shock, but usually lives above the subsistence line,

$$i_h^* - \Delta i_h(t) < c_{sub} \text{ and } i_h^* > c_{sub},$$
goes follows a type 3 recovery path consisting of three recovery modes (Fig. S3c). Starting below subsistence line, the household recovers at the standard recovery rate for people living under subsistence line \( R_{\text{sub}} \) until it reaches the subsistence line. Thus, in the case of recovery below subsistence line we can set \( \lambda_{h}^{R} = R_{\text{sub}} \). When the subsistence level is reached at time \( t_{\text{sub}} \) it recovers such as a type 2 household,

\[
\Delta k_{h}^{\text{eff}}(t) = \begin{cases} 
0, & \text{if } i_{h}^{*} - \Delta i_{h}(t) < c_{\text{sub}}, \\
\Delta k_{h}^{\text{eff}}(t) - \lambda_{h}^{R}(t), & \text{if } i_{h}^{*} - \Delta i_{h}(t) > c_{\text{sub}} \geq i_{h}^{*} - \Delta i_{h}(t) - \lambda_{h}^{R} \Delta k_{h}^{\text{eff}}(t), \\
\Delta k_{h}^{\text{eff}}(t_{\text{cep}})e^{\lambda_{h}^{R}(t-t_{\text{cep}})}, & \text{if } i_{h}^{*} - \Delta i_{h}(t) - \lambda_{h}^{R} \Delta k_{h}^{\text{eff}}(t) > c_{\text{sub}}.
\end{cases}
\]

A type 4 household already lives below the subsistence line in the steady state, \( i_{h}^{*} < c_{\text{sub}} \). We assume that it recovers with the average savings rate for households living under the subsistence line (Fig. S3d),

\[
\Delta k_{h}^{\text{eff}}(t) = \max\left[0, \Delta k_{h}^{\text{eff}}(t_{\text{shock}}) - R_{\text{sub}}(t - t_{\text{shock}})\right].
\]

**Consumption losses smoothed by precautionary savings**

We assume that type 1 and type 4 households plan the spending of their precautionary savings directly after each shock and do not change it until they have recovered or a new shock arises. Type 2 and type 3 households change their recovery pathway within the recovery phase and optimize their spending of savings each time when they enter a new recovery phase. After complete recovery, households start to set aside precautionary savings until they have reached the steady state level equaling their income net of expenditure (income surplus) for one year. We assume that households regrow their precautionary savings with a monthly rate of one twelfth of this surplus so that they recover within one year if not subject to further shocks.

**Type 1 recovery.** If a household is on a type 1 recovery track, it can estimate its expected cumulative consumption losses and already at \( t_{\text{shock}} \) and the expected losses it can smooth with its precautionary savings (cf. Fig. S3a). The consumption losses before smoothing with savings are the sum of its income losses \( \Delta i_{h}(t) \) (Eq. 11) and its consumption losses due to recovery efforts \( \Delta c_{h}^{\text{rec}}(t) \) (Eq. 10). Inserting Eq. 9 in Eqs. 10 and 11, we see that when neglecting the income from social transfers \( \left( i_{h}^{R}, c_{h}^{R}\right) \) household consumption in the absence of precautionary savings recovers exponentially,

\[
\Delta c_{h}^{\text{ns}}(t) = \Delta c_{h}^{\text{ns}}(t_{\text{shock}}) e^{-\lambda_{h}^{R}(t-t_{\text{shock}})}, \quad \text{Eq. 15}
\]

where we have introduced the consumption losses directly after the shock as \( \Delta c_{h}^{\text{ns}}(t_{\text{shock}}) = \left( (1 - \delta_{\text{sp}})\pi + \lambda_{h}^{R}\Delta k_{h}^{\text{eff}}(t_{\text{shock}}) \right) \). By integrating Eq. 15 over time, we see that in the limit of full recovery \( t \to \infty \), the cumulative expected consumption losses without savings are given by \( \Sigma_{h} = \Delta c_{h}^{\text{ns}}(t_{\text{shock}})/\lambda_{h}^{R} \). If the cumulative expected consumption losses can be smoothed by the precautionary savings, \( \Sigma_{h} \leq s_{h}(t_{\text{shock}}) \), the household employs them to compensate for consumption losses in every time-step of the recovery phase. If expected cumulative consumption losses are larger than its precautionary savings there remains a floor level of consumption losses \( s_{h}^{f} > 0 \) that cannot be smoothed by savings. To calculate this floor level, we first invert Eq. 15 to write the time spent in recovery as a function of the consumption losses,
\[ t(\Delta c_h^{rs}) = -(\lambda_h^{ti})^{-1} \ln \left( \frac{\Delta c_h^{rs}}{\Delta c_h^{rs}(t_{\text{shock}})} \right). \]  

Eq. 16

Equating \( s_h(t_{\text{shock}}) \) to integrated consumption losses up to \( s_h^{f,1} \), yields an implicit analytic expression for \( s_h^{f,1} \),

\[
s_h(t_{\text{shock}}) = \int_{s_h^{f,1}}^{s_h(t_{\text{shock}})} t(\Delta c_h^{rs}) d\Delta c_h^{rs} = (\lambda_h^{ti})^{-1} \int_{s_h^{f,1}}^{s_h(t_{\text{shock}})} \ln \left( \frac{\Delta c_h^{rs}}{\Delta c_h^{rs}(t_{\text{shock}})} \right) d\Delta c_h^{rs} \]

\[ \leftrightarrow 0 = \frac{1}{\lambda_h^{ti}} \left( \Delta c_h^{rs}(t_{\text{shock}}) - s_h^{f,1}(\ln \left( \frac{\Delta c_h^{rs}(t_{\text{shock}})}{s_h^{f,1}} \right) + 1) - s_h(t_{\text{shock}}). \right) \]

Eq. 17

Finally, the resulting consumption losses under type 1 recovery accounting for smoothing with precautionary savings can be written as,

\[
\Delta c_h(t) = \begin{cases} 
\min \left[ s_h^{f,1}, \Delta c_h^{ns}(t_{\text{shock}}) e^{-\lambda_h^{ti}(t-t_{\text{shock}})} \right] & \text{for } \Sigma_h > s_h(t_{\text{shock}}), \\
0 & \text{else}.
\end{cases}
\]

Eq. 18

**Type 2 recovery.** In the quasi-linear part of the type 2 recovery, households update their recovery rate \( \lambda_h^{r2} \) in each point in time according to Eq. 14. However, since households cannot foresee future changes in their recovery rate \( \lambda_h^{r2} \), they form their expectation on the recovery of their asset, consumption, and income losses and assume that their recovery rate will remain at the present level \( \lambda_h^{r2}(t) = \lambda_h^{r2}(t_{\text{reco}}) \) for \( t > t_{\text{reco}} \). From Eq. 14, we see that this allows to write their expected asset damages as a linear function of time

\[
\Delta k_h^{eff}(t) = \Delta k_h^{eff}(t_{\text{reco}}) - \lambda_h^{r2}(t_{\text{reco}})(t - t_{\text{reco}}) \quad \text{for } t \geq t_{\text{reco}}.
\]

From Eqs. 10 and 11 it then follows that for \( t > t_{\text{reco}} \) expected consumption losses from reconstruction and income losses can be expressed as

\[
\Delta c_h^{reco}(t) = \lambda_h^{r2}(t_{\text{reco}})
\]

and

\[
\Delta i_h(t) = \max \left[ 0, \pi(1 - \delta_{sp}^{lax}) \left( \Delta k_h^{eff}(t_{\text{reco}}) - \lambda_h^{r2}(t_{\text{reco}})(t - t_{\text{reco}}) \right) \right],
\]

respectively, where we have set \( i_{sp}^{lax} = 0 \) in the equation for the expected consumption losses (cf. type 1 recovery). According to Eq. 7, the total consumption losses that households expect at time \( t_{\text{reco}} \) for any future time step of the quasi-linear reconstruction phase before smoothing by precautionary savings \( \Delta i_h(t) + \Delta c_h^{reco}(t) \) (cf. Eq. 7) can be express as

\[
\Delta c_h^{ns,2}(t) = \max \left[ 0, \Delta c_h^{ns,2}(t_{\text{reco}}) - \pi \lambda_h^{r2}(t_{\text{reco}})(1 - \delta_{sp}^{lax})(t - t_{\text{reco}}) \right].
\]

Eq. 19

The inverse relationship then reads,

\[
t(\Delta c_h^{ns,2}) = \frac{\Delta c_h^{ns,2}(t_{\text{reco}}) - \Delta c_h^{ns,2}}{\pi(1 - \delta_{sp}^{lax}) \lambda_h^{r2}(t_{\text{reco}})}.
\]

Eq. 20
We now can calculate the floor level of consumption that remains after smoothing with precautionary savings, analogously to the type recovery (cf. Eq. 17), yielding the following quadratic relation for \( S_{h}^{2} \),

\[
0 = \frac{S_{h}^{2}}{2} - \frac{S_{h}^{2} \Delta c(t_{reco})^2}{2} - \pi \lambda_{h}^{2} (t_{reco}) (1 - \delta_{sp}) S_{h}(t_{reco}).
\]  
Eq. 21

Solving for \( S_{h}^{2}(t_{reco}) \) and choosing "-" branch then allows to write \( S_{h}^{2}(t_{reco}) \) as,

\[
S_{h}^{2}(t_{reco}) = \Delta c_{h}^{ns}(t_{reco}) - \sqrt{2\pi \lambda_{h}^{2}(t_{reco}) (1 - \delta_{sp}) S_{h}(t_{reco})}.
\]  
Eq. 22

Again, it is important to note that the floor level is calculated in each time-step of the quasi-linear recovery phase, which is why \( S_{h}^{2} \) is time dependent. The solution for the exponential phase of the type 2 recovery can be obtained as for a type 1 household. Thus, the recovery path of the consumption of a type 2 household can be written as,

\[
\Delta c_{h}(t) = \begin{cases} 
\max \left[ S_{h}^{2}(t), 0 \right] & \text{if } i_{h}^{r} - \Delta i_{h}(t) - \lambda_{h}^{2} \Delta k_{h}^{eff}(t) < c_{sub}, \\
\min \left[ S_{h}^{1}, \Delta c_{h}(t_{exp})e^{-\lambda_{h}^{1}(t-t_{exp})} \right] & \text{if } \Sigma_{h} > s_{h}(t_{exp}) \text{ and } i_{h}^{r} - \Delta i_{h}(t) - \lambda_{h}^{1} \Delta k_{h}^{eff}(t) > c_{sub}, \\
0 & \text{else},
\end{cases}
\]

where \( t_{exp} \) is the point in time from which type 1 recovery is possible (cf. Eq. 15).

**Type 3 recovery.** Households of recovery type 3 start their recovery below subsistence line where they recover with a constant rate \( \lambda_{h}^{2} = R_{sub} \). In this phase they do not experience additional consumption losses due to recovery efforts as \( R_{sub} \) is assumed to be the amount they save in normal times. Thus, \( \Delta c_{h}^{eco}(t) = 0 \) and their expected non-smoothed consumption losses at any time \( t \geq t_{shock} \) of the recovery phase can be written as,

\[
\Delta c_{h}^{ns,3}(t) = \Delta i_{h}(t) = \max \left[ 0, \pi (1 - \delta_{sp}) (\Delta k_{h}^{eff}(t_{shock}) - R_{sub} (t - t_{shock})) \right].
\]

The solution for the floor consumption level in this phase \( S_{h}^{3} \), can be derived analogously the relation obtained for the quasi-linear recovery phase of a type 2 household (Eq. 19-22) The only difference is that \( R_{sub} \) is in contrast to \( \lambda_{h}^{2} \) not time dependent. In consequence, the floor level of consumption is constant throughout the recovery phase,

\[
S_{h}^{3} = \Delta c_{h}^{ns,3}(t_{shock}) - \sqrt{2\pi R_{sub}(1 - \delta_{sp}) S_{h}(t_{shock})}.
\]

Since the second and third phase of a type 3 recovery correspond to type 2 recovery, the consumption losses in the recovery phase of type 3 household after smoothing with its precautionary savings can be written as
Type 4 recovery. Type 4 households always live under the subsistence line. This is why their recovery is analogous to the first recovery phase of a type 3 household. Thus, their recovery of consumption after smoothing with precautionary savings reads,

\[
\Delta c_h(t) = \begin{cases} 
\min \left[ s_h^f(t), \Delta c_h^{n3}(t) \right] & \text{if } \Sigma_h > s_h(t_{\text{shock}}) \text{ and } i_h^* - \Delta i_h(t) < c_{sub}, \\
\max \left[ s_h^f(t), 0 \right] & \text{if } i_h^* - \Delta i_h(t) > c_{sub} \geq i_h^* - \Delta i_h(t) - \lambda_h^1 \Delta k_{eff}^f(t), \\
\min \left[ s_h^f(t), \Delta c_h^{n3}(t_{\text{exp}}) e^{-\lambda_h^1(t-t_{\text{exp}})} \right] & \text{if } \Sigma_h > s_h(t_{\text{exp}}) \text{ and } i_h^* - \Delta i_h(t) - \lambda_h^1 \Delta k_{eff}^f(t) > c_{sub}, \\
0 & \text{else.}
\end{cases}
\]

Calculation of well-being losses

Finally, we derive the households’ total accumulated well-being losses from Eq. 10 by subtracting the accumulated utility gained under reduced consumption from an unperturbed consumption pathway,

\[
\Delta W_h(t_{sim}) = \frac{1}{1 - \eta} \int_0^{t_{sim}} \left[ (c_h^*)^{1-\eta} - c_h(t)^{1-\eta} \right] dt = \frac{1}{1 - \eta} \left[ (c_h^*)^{1-\eta} t_{sim} - \int_0^{t_{sim}} c_h(t)^{1-\eta} dt \right].
\]

For the calculation of overall well-being losses \( t_{sim} \) equals the full runtime of the model and we set the future discount rate \( \rho \) introduced in Eq. 6 to zero because otherwise we would give greater relevance to earlier shocks. In some cases not all of the savings are spent on the first shock, as households cannot plan with the recovery of income from social transfers \( i_{sp} \), but only for the recovery of their own asset stock.

Calculation of Socioeconomic Resilience

The socioeconomic resilience of a household is expressed by the ratio of asset damages to well-being losses \( \eta \). Therefore, we need to express the well-being losses in monetary terms. To this end we introduce the consumption losses equivalent as the consumption losses that an individual earning the national mean income would suffer,

\[
\Delta C_{equ}^c = \frac{\Delta W_h}{W'}, \quad \text{with } W' = \frac{\partial W}{\partial c} \bigg|_{c_{av}} = \frac{\partial}{\partial c} \bigg|_{c_{av}} \frac{c^{1-\eta}}{1 - \eta} = (c_{av})^{-\eta},
\]

where subscript \( c_{av} \) denotes the national average per-capita consumption. Thus, if a disaster causes 1 PHL Peso in well-being losses, it means that its wellbeing impact is equivalent to a 1 PHL Peso decrease in the consumption of the average Filipino. This allows us to express well-being losses, like asset damage, in monetary terms and use both metrics to define the household’s socio-economic resilience as,

\[
P_h^{soc} = \frac{\sum_{h=0}^{n_h} \sum_{\text{shocks}} w_h \Delta k_{eff}^f(t_{\text{shock}})}{\Delta C_{equ}^c}. 
\]
Derivation of flood forcing

To obtain a good representation of the flood shocks with regard to coverage and timing, we make use of flood records from satellite images and event recordings from the EM-DAT database and build shock time series for individual households. Household attributes such as income, location (region) and asset vulnerability are extracted from the FIES such that the model agents represent the entire population of the Philippines.

The flood shocks are modeled as specific time stamps at which the households affected by the event are shocked. The agents are modeled over a time period of 16 years where households can experience shocks complemented by an additional period afterwards until all households have fully recovered (160 years). Beginning in 2002, flood events take place at the event dates given in Table S2. The time resolution of the model is four weeks, so events that lie within four weeks are modeled as one event.

We apply a three step procedure to generate a historical time series of flood affected households: we i) intersect the GFD flood maps with the population map to determine all flood affected grid cells, ii) distribute individual households from survey data to grid cells to simulate the exact location of the households, and iii) derive affected households from the flooded grid-cells to match the number of affected people recorded in EM-DAT.

In step i), we use the open source climate impact modeling tool CLIMADA to generate maps of exposed population for each flood event. As input data, we use the satellite maps from the Global Flood Database (GFD) and the population map from 2015 from the gridded-population-of-the-world (GPW v4) dataset. For step ii), we use the union of flooded populated grid-cells from all events to distribute households included in the FIES according to the population given in GPW in each populated flooded grid-cell. For each region we select all households sampled in this region from the FIES. The households are distributed as diversely as possible to each flooded grid cell. We cannot make any reasonable assumptions about income differences between single grid cells within one region, so we aim to fill grid cells with heterogeneous households. As sampled households have an assigned weight and represent a group of households of the same type, we “unpack” each group of households, receiving several single households with the same characteristics. We fill each flooded grid cell with single households from different groups, such that there are as few households with the same characteristics as possible. The remaining households are considered as being located outside the affected areas. They are not shocked, but are also included in the model simulation with their remaining weights as they contribute to the consumer tax revenue of the government. Comparing data records from EM-DAT with the total number of affected people generated by the intersection of the flood map with the population data, we find that usually the number of people in all affected grid cells exceeds the number of affected people recorded in EM-DAT (cf. Tab. S2). Therefore, we introduce step iii) and calibrate the model for each event to the number of affected people given in EM-DAT (cf. Model calibration). For each event, we calculate the ratio of affected people in the EM-Dat and the exposed population calculated with CLIMADA. We apply the resulting fraction as a probability of being flooded on each grid cell and randomly choose only the fraction of households from all households located in the grid cell (Tab. S2). To generate one realization of a shock time series, steps i) — iii) are repeated for all events. In total, we generate 25 different shock time series by repeating the household distribution step ii) to investigate the robustness of our work.

Model calibration

In Tab. 1, we provide an overview of all the parameters calibrated to run the model. The number of flood shocks, their time distance and the number of affected households is calibrated to the number of affected people given in EM-DAT as described in Sec. Derivation of flood forcing. In the absence of shocks, the model is in a steady state. The steady state values of the key household variables income from productive assets \( i^*_h \), income form social spendings \( i^{sp}_h \), and precautionary savings \( s^*_h \) are
taken from the income and expenditure data of the FIES survey. We also estimate the recovery spending of people living under the subsistence line $R_{sub}$ from the FIES by calculating the average annual savings, as difference between income and expenditure, of all households living under subsistence line. Additionally, for each household, we estimate its asset vulnerability $v_h$ according to the building structure given in the FIES. The survey distinguishes between robust, moderate, and fragile buildings. We assume that this building quality is valid for all of the household’s assets and assign corresponding vulnerabilities, for each household we simulate a random variation within the uncertainty range around the basic vulnerability factor (Tab. 1).

**Code availability**

All the source code required to reproduce the results of this work is available at https://github.com/ingajsa/hhwb.

**Data availability**

All the data used to produce this research is publicly available. The FIES 2015 needs to be requested from the Philippines Statistical Authority.

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Figures and Tables

Figure 1: Exposure of the Philippines to floods. a Regions of the Philippines (colored boundaries) and number events in each grid cell over the period 2000-2018 as reported by the Global Food Database 2021 (color code), b population numbers, c mean per capita income for each region according to FIES 2016 survey [35], and d flood affected people over the period 2000-2018 as estimated from Global Flood Database [42].
Figure 2: Modeled recovery dynamics for an individual household. **a** Recovery dynamics in the aftermath of an individual event (left column) and multiple events (right column). Damage to the stock of productive assets, losses in total income (sum of income generated from assets and social transfers), consumption losses, and cumulative well-being losses (top to bottom). Consumption losses are driven by income losses (purple area) and reconstruction investments to rebuild destroyed assets (orange area). Dashed and full lines indicate recovery dynamics without and with the opportunity of smoothing consumption losses with savings, respectively. **b** Comparison between the recovery dynamics of the productive asset stock for the factual scenario where households can be affected multiple times (left column) and the counterfactual scenario 1 where shocks are distributed across households such that each household is affected at most once (right column). **c** Comparison between the factual scenario (top) and the counterfactual scenario 2 where the time between shocks is artificially extended so that affected households can always fully recover their assets in-between shocks (bottom).
Figure 3: Nationally aggregated response dynamics to observed flood sequence. a Temporary evolution of the damage to the stock of productive assets, b consumption losses, and c accumulated well-being losses aggregated over all households to the national level for subsequent flood shock over the period 2000-2018 covered by the Global Flood Database\textsuperscript{42}. The black and red line indicate the factual scenario where the same households can be affected by several floods and a counterfactual scenario where households are affected only once, respectively. Gray vertical lines indicate flood events as recorded in the Global Flood Database from January 1, 2002 to January 1, 2018 (white background). The recovery phase where no further shocks are recorded as the time period is no longer covered by the Global Flood Database is indicated in blue. Dash-dotted lines in c indicate the relative difference between the well-being losses for the factual and the respective counterfactual scenarios. Yellow and purple lines in c indicate scenarios where households do not have savings to mitigate consumption losses. Well-being losses are measured in well-being loss units (WBLU) (Methods).
Figure 4: Distributional and regional impacts of recurrent flood shocks. Average cumulative direct asset damages (panel a), average cumulative consumption losses (panel b), average share of their lifetime flood affected households in the Philippines spend recovering their damaged assets from recurrent flood shocks as reported by the Global Flood Database over the period 2000-2018 (panel c), average cumulative well-being losses measured in well-being loss units (WBLU) (panel d) and average socioeconomic resilience (panel e). Left column: National averages for each per-capita income decile of the population for the factual scenario where the same household can be affected multiple times (solid black lines) and the counterfactual scenario 1 where each household can be affected at most once (solid orange lines). Absolute (left y-achses) and relative differences (right y-achses) between the factual and the counterfactual scenarios as they arise from incomplete recovery in between events in the factual scenario are denoted by dashed purple lines. Whiskers denote 90% uncertainty intervals as established from 25 runs with varying household selections (Methods). Middle column: Regionally differentiated variable values as obtained for factual scenario (color code). Right column: Same as middle column but for differences between factual and counterfactual scenario 1.
Figure 5: Distributional effects for households in dependence of the number of floods they experience. **Left column:** Average cumulative direct asset damages (**panel a**), average cumulative consumption losses (**panel b**), and average cumulative well-being losses (**panel c**) for households in each income decile that are affected by 1-5 flood events in the period 1980-2018 covered by the Global Flood Database in the factual scenario. **Middle column:** Average increase in losses with the number of flood events that households experience relative to the average losses of households that are affected only by one flood event. Horizontal green lines indicate damages and losses that would occur if losses increased linearly with event number. **Right column:** Relative increase in average losses in the factual scenario where households may not recover between events compared to the counterfactual scenario where full recovery is always possible. Absolute well-being losses are measured in well-being loss units (WBLU) (Methods).
Table 1: Summary of all calibrated parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Abbreviation</th>
<th>Value</th>
<th>Source</th>
<th>Unit/Format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Event dates</td>
<td>–</td>
<td>–</td>
<td>GFD (Tab. S2)</td>
<td>yyyy-mm-dd</td>
</tr>
<tr>
<td>Affected people of each event</td>
<td>–</td>
<td>–</td>
<td>EM-DAT (Tab. S2)</td>
<td>persons</td>
</tr>
<tr>
<td>Household income</td>
<td>$i^*_h$</td>
<td>–</td>
<td>FIES</td>
<td>$PHL \text{ Pesos} \text{ year}^{-1}$</td>
</tr>
<tr>
<td>Household income from social transfers</td>
<td>$i^*_{sp,h}$</td>
<td>–</td>
<td>FIES</td>
<td>$PHL \text{ Pesos} \text{ year}^{-1}$</td>
</tr>
<tr>
<td>Consumption at subsistence line$^{35}$</td>
<td>$c_{\text{sub}}$</td>
<td>15925</td>
<td>FIES</td>
<td>$PHL \text{ Pesos} \text{ year}^{-1}$</td>
</tr>
<tr>
<td>Recovery spending of people under subsistence line</td>
<td>$R_{\text{sub}}$</td>
<td>3339</td>
<td>FIES</td>
<td>$PHL \text{ Pesos} \text{ year}^{-1}$</td>
</tr>
<tr>
<td>Precautionary savings</td>
<td>$s^*_h$</td>
<td>–</td>
<td>FIES</td>
<td>$PHL \text{ Pesos} \text{ year}^{-1}$</td>
</tr>
<tr>
<td>Household vulnerability</td>
<td>$\nu_h$</td>
<td>Derived from FIES building standards: robust = 0.14 ± 0.06, moderate = 0.4 ± 0.08, fragile = 0.7 ± 0.14</td>
<td>FIES and Walsh and Hallegatte 2020$^{11}$</td>
<td>–</td>
</tr>
<tr>
<td>Planning horizon</td>
<td>$T_p$</td>
<td>15</td>
<td>Extended from Walsh and Hallegatte 2020$^{11}$</td>
<td>years</td>
</tr>
<tr>
<td>Total runtime</td>
<td>$T_{\text{sim}}$</td>
<td>162</td>
<td>Time until all households have fully recovered</td>
<td>years</td>
</tr>
<tr>
<td>Productivity of capital$^{11}$</td>
<td>$\pi$</td>
<td>0.33</td>
<td>Adopted from Walsh and Hallegatte 2020$^{11}$</td>
<td>–</td>
</tr>
<tr>
<td>Elasticity of the marginal utility$^{11}$</td>
<td>$\eta_l$</td>
<td>1.5</td>
<td>Adopted from Walsh and Hallegatte 2020$^{11}$</td>
<td>–</td>
</tr>
<tr>
<td>Future discount rate$^{11}$</td>
<td>$\rho$</td>
<td>0.06</td>
<td>Adopted from Walsh and Hallegatte 2020$^{11}$</td>
<td>$\frac{1}{\text{year}}$</td>
</tr>
</tbody>
</table>
Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- supplementaryinformationrecurrrentfloods.pdf