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Global economic response to river floods

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Increasing Earth's surface air temperature yields an intensification of its hydrological cycle[1]. As a consequence, the risk of river floods will increase regionally within the next two decades due to the atmospheric warming caused by past anthropogenic greenhouse gas emissions[2–4]. The direct economic losses[5,6] caused by these floods can yield regionally heterogeneous losses and gains by propagation within the global trade and supply network[7]. Here we show that, in the absence of large-scale structural adaptation, the total economic losses due to fluvial floods will increase in the next 20 years globally by 17% despite partial compensation through market adjustment within the global trade network. China will suffer the strongest direct losses, with an increase of 82%. The United States is mostly affected indirectly through its trade relations. By contrast to the United States, recent intensification of the trade relations with China leaves the European Union better prepared for the import of production losses in the future.

Damages caused by anthropogenic greenhouse gas emissions may become a significant factor within the global economy[8–11]. Among the most significant climatic changes are those in the hydrological cycle. The global mean temperature has increased by about 1 °C during the past century and will increase by the same amount within the next 20 to 30 years (Supplementary Fig. 1 adopted from ref.[1]). Atmospheric warming yields higher evaporation and thereby increased global precipitation. At the same time, a warmer atmosphere can carry more water vapour, which may lead to enhanced heat and moisture transport and an intensification of strong rainfall events[1]. Regionally, this may yield an increase in fluvial flood risk[12,13], especially, but not exclusively, in Southeast Asia[3]. Depending on local flood protection, more severe events can destroy economic assets and infrastructure (referred to as asset damages in the following) and hamper economic production. We here refer to the latter, missed production as the direct losses caused by the adverse events. Within the global network of supply chains and trade relations, regional production reduction affects economic sectors elsewhere via supply shortages, changes in demand, and associated price signals[14,15]. These indirect losses can spread even beyond first-tier connections (that is, firms directly linked to affected regions[7]), which poses additional climate risk on the global economy[16]. At the same time, the economic network allows for market adjustments that can dampen economic losses, for example, by shifting demand to non-affected suppliers[17]. Prices react even in the short-term, and thus play a crucial role in redistributing production[18]. Accordingly, the total losses, defined as the sum of direct and indirect losses of an adverse event, can be larger or smaller than the direct losses, depending on the response of the economic network to the disturbance.

Using projections of near-future fluvial floods until the year 2035, we calculate the associated direct production losses and their indirect repercussions in the global economic network. In these two decades to come, the global temperature evolution is dominated by the past carbon emissions. Accordingly, differences in climate projections for different emission pathways are within the range of model uncertainty (Supplementary Fig. 1). In the Supplementary Information we demonstrate the robustness of our results with respect to changes in the specific choice of model and parameter set. We here employ climate projections for the representative concentration pathway (RCP) 2.6 of the five global coupled climate model simulations of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP; see Methods). Using fixed socio-economic conditions, we derive an ensemble of daily time series for flood events and calculate the direct production losses they cause; herein, we assume only non-service sectors to be affected. On the same daily timescale, we compute from these direct losses the indirect and total losses using a deterministic loss-propagation model on the 2012 global economic network. During the first decade of the twenty-first century, the global economic network has undergone strong structural changes relevant for the global economic dynamics[15,19]. To investigate the role of these changes we carry out additional simulations with the baseline network of the year 2002. Throughout this study, we present the results for time periods of twenty years. This double-decade time span was chosen as a compromise that allows us to capture trends in time, but averages over specific dynamic events, such as single floods and economic parameter uncertainty.

In the following, we look at the average of the model ensemble. Results for the particular model runs are shown in the Supplementary Information. Within this modelling framework, changes in the hydrological cycle result in a strong increase in globally aggregated direct losses due to fluvial floods (Fig. 1 in accordance with ref. [2]). These losses are projected to increase from US$208 billion in 1976–1995 via US$351 billion in 1996–2015 to US$597 billion in 2016–2035. All currency values that are provided here are in US dollars of the particular year of the economic network data used (that is, 2012 unless stated otherwise). These losses result entirely from reduced productive capacity, for example, due to flooded regional sectors. Additional economic damage may occur when assets are permanently damaged, an impact which is not captured here[20].

Large direct losses are observed in China, the United States, Canada, India, Pakistan and various countries of the European Union (Fig. 2). This implies that—with the current level of regional river protection (that is, without further adaptation efforts)—large parts of highly populated areas will experience floods in the future due to an increase in precipitation extremes. The largest share of this increase is projected to arise in China (Fig. 3b). Here, we find US$214 billion in production losses in 1996–2015 (US$126 billion in 1976–1995) and project these losses to increase by 82% to US$389 billion in 2016–2035, which corresponds to about 5% of China's annual 2012 gross domestic product (GDP). Particularly affected are China's eastern and coastal regions of Jiangsu and

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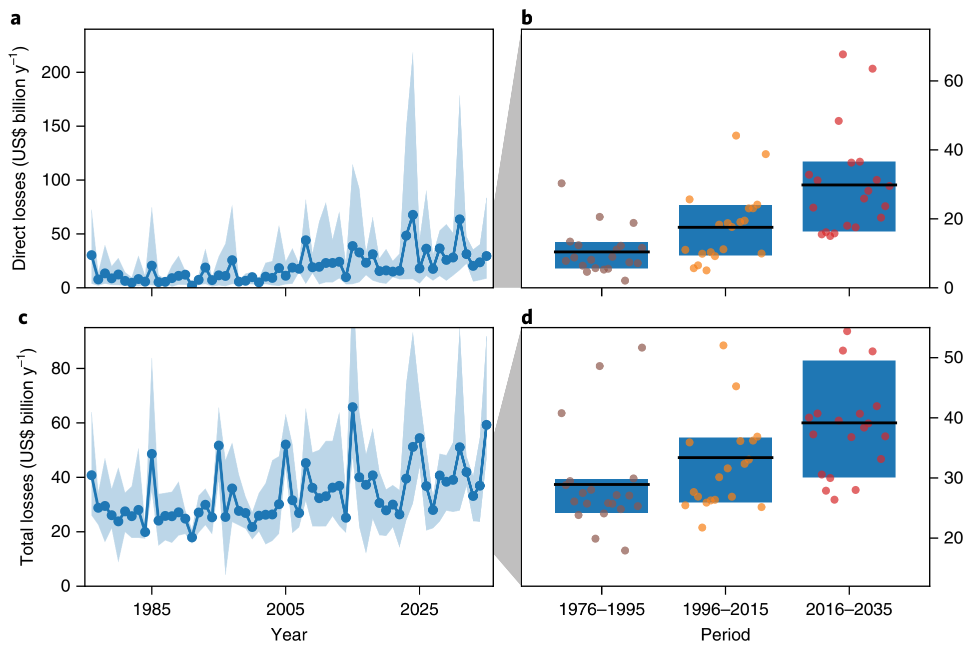

Fig. 1 | Increase in economic losses due to fluvial floods in economically strong and populated areas. a,**b**, Direct annual losses per year, global aggregate. **c**,**d**, Total annual losses per year, global aggregate. **a**,**c**, Respective time series. Solid lines are the model ensemble mean, shaded areas denote the minimum and maximum of the ensemble. **b**,**d**, Respective mean and likely range (16.7 to 83.3 percentiles) over the annual data points of the ensemble mean per double-decade (brown, yellow and red points).

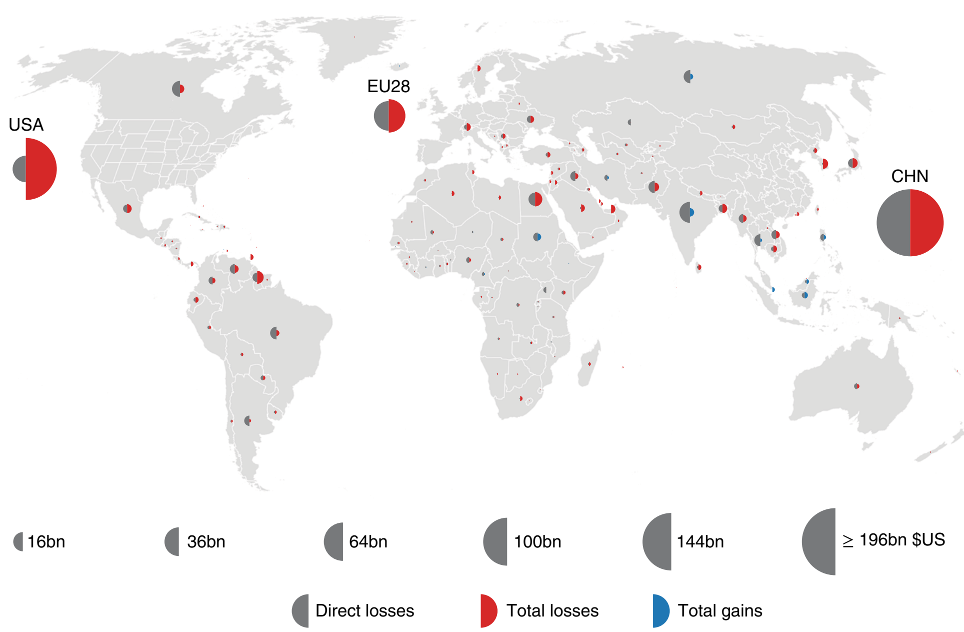

Fig. 2 | Losses and gains between 2016 and 2035. Half-circles to the left (grey) represent direct losses, those to the right indicate total losses (red) or net gains (blue). China (CHN), the United States (USA) and the European Union (EU28) are represented as aggregates over their respective subregions, other regions are represented by half-circles at the centroid of the respective largest continuous land mass. All regions shown are those used in the loss-propagation model, each including 26 sectors and one regional final consumer. We provide more detailed information for each double-decade focused on in this study in Supplementary Fig. 5 and an animation for the entire time period in the Supplementary information. Values denote the model ensemble mean.

Zhejiang, which are among China's most populated and economically strongest provinces. These results are well in line with studies predicting additional pressure from precipitation and fluvial flood events in East and Southeast Asia[3,21].

Regional sectors that are directly impacted by flood events react by reducing their demand, adjusting their potential purchase price, and by communicating higher production costs for increased production downstream the trade chain. As a consequence, other regional sectors are affected indirectly and have to respond to these changes. In many cases, this leads to cascading indirect losses due to reduced demand and further supply shortages. However, since regional sectors have the flexibility to increase their production

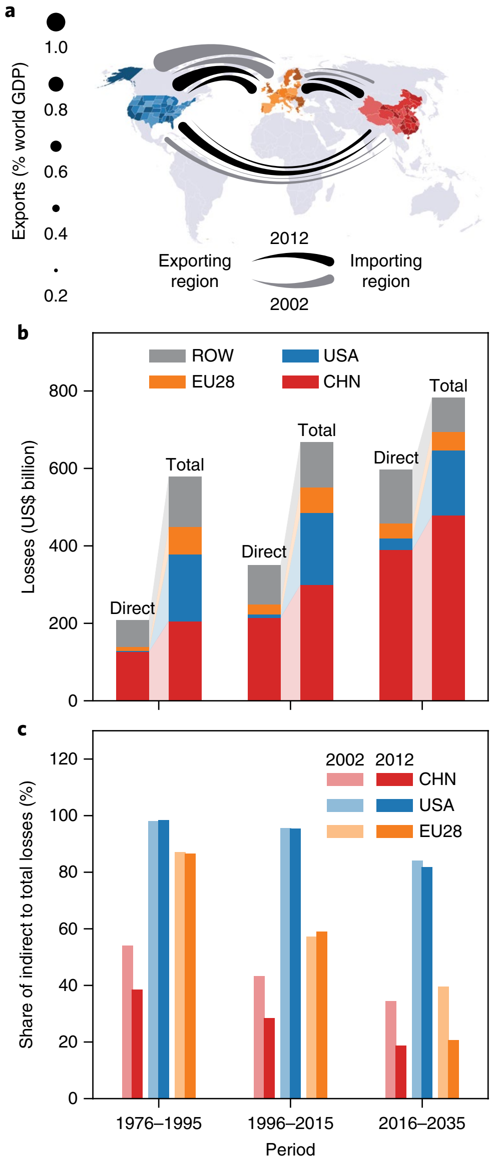

Fig. 3 | Losses propagated through trade relations for key regions. a, Export–import relations for 2002 and 2012 as a percentage of world GDP (of the corresponding year) for the three main economic regions discussed in this study. Sizes are given by the larger end of the cones. Exports from the United States (USA) to China (CHN) have not grown as much as the other trade relations from 2002 to 2012, increasing the imbalance in trade between China and the United States (see time series in Supplementary Fig. 4). **b**, Direct versus total losses for the key regions China, United States, European Union (EU28) and the rest of the world (ROW). **c**, Ratios of indirect losses to total losses as obtained for the economic network of 2002 (light colours) and that of 2012 (darker colours). Values denote the model ensemble mean.

level in scarcity situations, local production failures can be mitigated by unaffected regional sectors. For shocks that are not too large, the global economic system thus has the flexibility to adjust and dampen the shocks caused by flood events (Fig. 3).

This market adjustment is highly spatially heterogeneous. The global buffering of direct losses leads to net gains in some regions, especially in Southeast Asia, Oceania, and India (Figs. 2 and 3). In the United States, by contrast, indirect losses are significantly higher than direct losses. In 1976–1995 they exceed direct losses by US$169 billion (by US$177 billion in 1996–2015 and by US$137 billion in 2016–2035). This is in stark contrast to the severely directly affected China, which suffers only US$90 billion additional indirect losses in 2016–2035, albeit experiencing US$389 billion of direct losses, two-thirds of the overall losses in that period.

The fact that the United States is not profiting from market adjustment can be traced back to the particular role of the United States in the economic dynamics within the trade network. In computations with the same climatic forcing, but with the economic network of the year 2002, the United States remains highly impacted through its trade relations (Fig. 3c). By contrast, the European Union experiences significantly larger indirect losses within the 2002 network than within the 2012 network. Whereas for the European Union the share of indirect to total losses drops from 40% for the 2002 to 21% for the 2012 economic structure, this value remains high for the United States, with about 82% for 2016–2035, above 98% for 1976–1995, and around 95% for 1996–2005. Thus, the European Union benefits much more from market adjustment in the 2012 network than in the 2002 network. As the differences between these two economic data sets are less pronounced for 1976–1995 (87%/87%) and 1996–2015 (57%/59%), it is the future increase in flood events in China that the European Union is well adjusted for. The reason for this can be found in the trade volume between these three economic regions, as detailed below (Fig. 3a, detailed time series in Supplementary Fig. 4).

During the projected double-decade 2016–2035, direct losses in China (Fig. 4b) result in associated total production losses (Fig. 4d) within the country, but in small total production gains in the European Union. This is caused by an increased export from the European Union to China (Fig. 4f). This effect is significantly smaller within the economic situation of 2002 (Fig. 4a,c,e). Although the United States shows a qualitatively similar dynamic response to Chinese floods, the magnitude is too small to result in a net gain.

These results can be explained by continuous connectivity increases of the global economy within the past two decades[15] affecting regional economies in two counteracting ways. On the one hand, a higher connectivity can foster the cascading of indirect losses along global supply chains, enhancing total production losses[19]. On the other hand, as observed here, more intense trade can help to mitigate losses by facilitating market adjustments. If one supplier is impacted by a disaster, a larger supplier base increases the chance that other suppliers can temporarily replace the affected one. For example, a regional sector with a small supplier base can substitute supply failures less well than a regional sector having a large supplier base of equally important suppliers. Also, an unaffected regional sector can benefit from a disaster by substituting affected competitors. Accordingly, direct losses can be either amplified or partially compensated for in the disaster aftermath. Which of these effects dominate in a region depends strongly upon the interplay of three factors: flood pattern and flood severity; the position of the region in the trade network (hub versus peripheral node); and the nature of the trade relations (balanced versus unbalanced).

These computations stress the importance of the network characteristics of the trade relations for the magnitude of the indirect losses. The balanced trade relations between the European Union and China are more advantageous for loss mitigation than the unbalanced situation between the United States and China. Although the United States and the European Union are affected by Chinese supply-chain losses to a similar extent (Fig. 3a), the European Union has a competitive advantage when it comes to exports to China; since there are stronger trade relations between the European Union and China than between the United States and China (Fig. 4e,f), the European Union is in a better position to increase exports and temporally replace affected Chinese producers. It is worth noting that balanced trade relations are also advantageous for the trade partner that is more strongly directly affected by floods (that is, China).

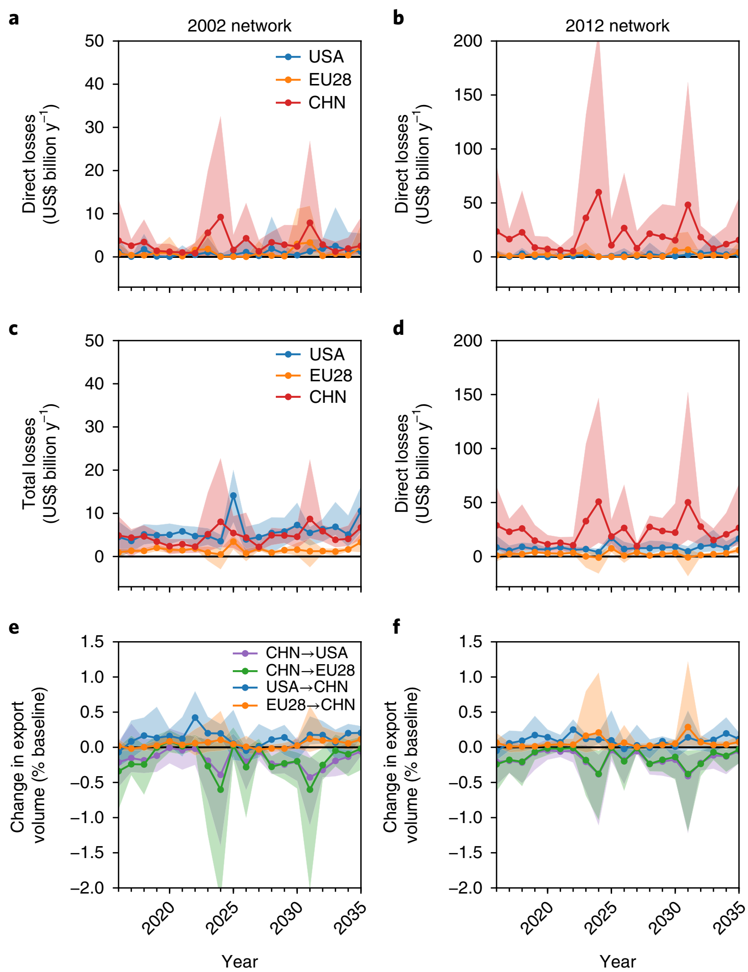

Fig. 4 | Temporal evolution for two different economic network constellations. a,**c**,**e**, 2002 network. **b**,**d**,**f**, 2012 network. Solid lines denote the model ensemble mean and shaded areas the minimum and maximum of the ensemble. Floods in China (CHN) cause direct production losses locally in China (**a**,**b**). These are partially compensated for in other parts of the world (**c**,**d**). As a consequence, the economic flow from China is reduced while the flow into China is enhanced (**e**,**f**). Between the years 2002 and 2012, the European Union (EU28) has increased exports to China while the United States (USA) has only done so very mildly (Fig. 3a). During flood years, the export from the European Union to China has thus intensified with the 2012 economic network compared to the 2002 situation (**e**,**f**).

The strong trade relations to the European Union help sectors in the Chinese economy that are not affected by floods to keep up production in the disaster aftermath and to avoid—or at least mitigate—indirect losses (Fig. 3c). By contrast, it is disadvantageous for China that, for the compensation of local outages, it cannot resort to US trade partners to the same extent in order to compensate for local outages.

In the model chain employed here, uncertainties quickly accumulate. The ensemble of climate projections already comes with an uncertainty range, which is further increased by the assumptions we have to make for the socio-economic factors. These are, in particular, the distribution of production and the direct response to flood events, including the recovery dynamics, which may be specific for different regions and economic sectors, and the response dynamics in the loss-propagation model. In modelling the real-world agents as regional sectors we assume a specific (here profit-optimizing) decision rationale. Imports and exports may deviate from their baseline levels given by input–output data and are only restricted by the limited availability of idle capacities and the existence of trade connections; that is, we assume the network structure to be static. The details of the Acclimate model are given in the Methods and ref. [22]. With these particular assumptions, the results are qualitatively robust under the uncertainties in the climate model ensemble and for different sets of affected sectors (Supplementary Figs. 2 and 3).

Our results for the future period have to be interpreted cautiously because economic growth and further economic concentration processes will change the relative economic importance of regions as well as their mutual inter-dependencies. These changes are not accounted for in this study, which focuses on the effect of changes in flood exposure due to climate change and the resulting adaptation pressure. In particular, we assume a constant population distribution, resulting in a constant distribution of production patterns. Socio-economic changes[23] have, however, been shown to further increase the regional flood risk in the future[6], which is likely to lead to higher exposure than assumed here.

In applying only two economic networks, those of 2002 and 2012, we can infer the role of a balanced and an imbalanced trade relation with China, but we might be missing the role of other important network characteristics which are not captured in the transition between 2002 and 2012. We can make statements only about the effects of the trend in the global trade network that occurred in this decade. In that, the US trade deficit with China has significantly increased (Fig. 3a). If this trend continues, we expect that the United States could, in the future, be even more vulnerable to Chinese supply-chain disruption than suggested by our simulations. In contrast, over the past two decades, European exports to China were able to catch up with the growth of Chinese exports to the European Union, thereby balancing trade relations (Fig. 3a). Our simulations suggest that building balanced trade relations might be a viable strategy to climate-proof regional economies. To make more detailed and quantitative projections about future direct and indirect losses, the climate scenarios would need to be accompanied by socio-economic ones, in particular for production and trade relations.

Our computations suggest that balanced trade relations help to protect a national economy against a global intensification of weather extremes.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available at https://doi.org/10.1038/s41558-018-0173-2.

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Author contributions

All authors designed the research. S.W. and C.O. developed the loss-propagation model. S.W. and A.L. conducted the analysis. All authors discussed the analysis and wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

Flood projections. From the physical impact side, we follow the method of Hirabayashi et al.[3], which we recently advanced upon[2]. We use the climate projections of five models from the Coupled Model Intercomparison Project Phase 5 (CMIP5)[24] with the historic and RCP2.6 scenarios on a daily timescale and an atmospheric resolution of 2° × 2.5° within the ISIMIP Fast Track[25]: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M. Their temperature and precipitation fields are bias-corrected towards an observation-based data set[26] using a trend-preserving method[27]. These drive the hydrological projections, for which we use the LPJmL model on a 0.5° grid[28,29], and which are further distributed along the river networks by the CaMa-Flood river routing model[30] with a spatial resolution of 0.005°. CaMa-Flood improves the accuracy of peak river discharge compared to the direct use of the output from the hydrological model[31].

To correct for regional biases in the models, we fit a generalized extreme value distribution to the time series of annual maximum discharge for the available historic period (1971–2004) using L-moment estimators. This yields the return period (in historic terms) for each event, allowing the incorporation of current, regionally distributed flood protection level data given in that spatial unit. Here, we rasterize the 'Merged Layer' of the FLOPROS database[32], which incorporates physical infrastructure, policy requirements and model results to derive protection-level data on a sub-national scale. This threshold procedure implies that, when the protection level is exceeded, the flood happens as if there was no protection in the first place (for example, dams break). This is analogous to studies that assume a fixed threshold, for instance, a 100-year return period. We then look up the return level—that is, flood depth—corresponding to the return period in a MATSIRO model[33] run driven by observed climate forcing[34]. Cells with a mean daily discharge of less than 0.1 mm d^{-1} in 1971–2004 are excluded. After downscaling flood depth and flooded area fraction to 0.005° resolution, we re-aggregate to a 2.5′ resolution. This procedure yields an ensemble of five representative daily time series of flood extents for the period of 60 years chosen in this study (1976–2035). With that we can explicitly capture concurrent flood events in different regions, as any correlation in particular events is the result of physical processes.

Production losses. The economic projections are carried out with the global loss-propagation model Acclimate[22,35,36] using a state-level resolution for the United States, province-level resolution for China, and a national resolution for the rest of the world. In the following, we refer to these more generally as regions. Acclimate is an anomaly model evolving around a baseline global economic network constituted from multi-regional input–output data (EORA simplified dataset v199.82[37]), which are comprised of annual monetary flows, interpreted as measure of quantity flows, between sectors and regions. As economic baseline year for the flows between the 7,236 regional sectors, we use 2002 and 2012 in two separate calculations.

Direct losses. To derive local production outages, we assume that production capacity is locally reduced by the same extent as the corresponding cell is flooded, regardless of flood depth. As a proxy for the distribution of production, we use the distribution of population. Accordingly, the flood fraction of each cell times the population count on the same resolution[38] yields daily time series of flood-affected people. For mapping grid cells to regions, we use the GADM database[39] rasterized to 2.5′ and advanced on coastal cells to incorporate the coastal population. We use these numbers relative to the total population per region as the production capacity reduction for a non-service sector subset of all sectors given by the input–output data (17 out of 26 economic sectors, given in Supplementary Table 1; results for simulations affecting all sectors are given in the Supplementary Information). All of these sectors are affected in equal measure. The absolute reduction in production output from the input–output table then yields the direct losses per day.

Here, we make no further assumptions about direct response or the recovery of production, but that it directly follows the flood extent with instantaneous recovery. By the nature of most flood events, this implies a slow onset, maximum losses and a retracting period back to no flood (that is, back to full production capacity). In this study, we further focus on the changing climate while keeping the economy constant. In particular, we assume that the population distribution does not change significantly in the next 20 years, and use the population data of 2010 for all runs[38].

Since China and the United States are of particular interest in this study and constitute the largest economies as single countries, we disaggregate these down to their provinces and states, respectively. This is done using the subregional shares of the gross regional product (GRP) while keeping the overall flows between regions consistent[40]. This not only refines the direct losses on the disaggregated regions, but also splits flows in the network so sub-national regions can be represented by individual agents in the loss-propagation model. For the European Union the national resolution represents a similar level of detail as the disaggregated representations of China and the United States.

Indirect losses. To derive the daily time series of indirect and total losses, we use the relative decrease in production capacity caused by the flood events as perturbative input for Acclimate, reducing the maximum possible production. Acclimate then simulates the behaviour of regional sectors and consumers when perturbed from the baseline by a demand, supply or price shock. In that, each regional sector, represented by a node in the input–output network, individually maximizes its profit by choosing the optimal production level and corresponding upstream demand as well as the optimal distribution of this demand among its suppliers. Transport and storage inventories act as buffers for supply shocks. Regional sectors may activate idle capacities when demand is particularly high, which comes with additional production costs. The model accounts for local price changes, and supply and demand mismatches are resolved explicitly over time. In the disaster aftermath, these relax back to the unperturbed baseline equilibrium over a timescale determined by the market. Computed losses thus account for price effects such as demand surge and supply shortages. A comprehensive model description of Acclimate is provided in Otto et al.[22].

Limitations. We take a rather simple approach to distribute production by using the population distribution as a proxy, which for instance does not account for land-use patterns. However, we believe this approach to be sufficiently good to distribute production losses on a rather aggregated national or state level. Also, as a first-order approximation, we assume flood protection to have no effect once the flood exceeds the protection level. Other studies, when computing asset losses, make use of depth-dependent damage functions[41,42]. This approach may result in better loss estimations, because it permits us to account for land-use patterns and the full effect of flood protection[43].

For computational reasons, we restricted our analysis to RCP2.6. As discussed above, the differences in the rise of global mean temperature for each RCP until 2035 are within the climate model ensemble spread. Nevertheless, the particular flood patterns might differ between concentration pathways, which cannot be accounted for in this study.

Code availability. The implementation of the Acclimate model is available as open source on https://github.com/acclimate/acclimate with identifier https://doi.org/10.5281/zenodo.853345, the implementation of the disaggregation algorithm can be found on https://github.com/swillner/libmrio (https://doi.org/10.5281/zenodo.832052), the flood processing procedure can be found on https://github.com/swillner/flood-processing (https://doi.org/10.5281/zenodo.891302).

Data availability. The data that support the findings of this study are available from the corresponding author upon request.

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