

<https://doi.org/10.1038/s43247-024-01401-y>

# Limited progress in global reduction of vulnerability to flood impacts over the past two decades

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Global flood impacts have risen in recent decades. While increasing exposure was the dominant driver of surging impacts, counteracting vulnerability reductions have been detected, but were too weak to reverse this trend. To assess the ongoing progress on vulnerability reduction, we combine a recently available dataset of flooded areas derived from satellite imagery for 913 events with four global disaster databases and socio-economic data. Event-specific flood vulnerabilities for assets, fatalities and displacements reveal a lack of progress in reducing global flood vulnerability from 2000–2018. We examine the relationship between vulnerabilities and human development, inequality, flood exposure and local structural characteristics. We find that vulnerability levels are significantly lower in areas with good structural characteristics and significantly higher in low developed areas. However, socio-economic development was insufficient to reduce vulnerabilities over the study period. Nevertheless, the strong correlation between vulnerability and structural characteristics suggests further potential for adaptation through vulnerability reduction.

Floods cause a considerable share of direct impacts from natural hazards (9% of fatalities, 23% of damages and 49% of displacements since 2008)<sup>1,2</sup>. In most world regions, the frequency and intensity of fluvial floods is projected to increase under ongoing global warming<sup>3</sup>. Water levels of fluvial floods are likely to be additionally augmented through rising sea levels in the future<sup>4</sup>. The compound risk posed by sea-level rise, more intense rainfall and average cyclone intensity is projected to intensify coastal floods caused by tropical and extratropical storms<sup>5,6</sup>. At the same time, there is medium to high confidence that future increases in heavy rainfall events and socio-economic changes will amplify the pluvial flood risk in several regions of the world<sup>7</sup>.

In addition, projected increases in exposure due to economic and population growth as well as increasing settlement in flood prone areas may act as additional drivers for surging flood risk<sup>8–10</sup>. Besides implementing stringent greenhouse gas (GHG) mitigation measures, it is essential to assess the potential of adaptation in reducing the impacts of climate change and to determine the extent to which these options are already implemented effectively. Climate change adaptation can target each of the three drivers of risk: hazard, exposure and vulnerability. In this work, we focus on adaptation through a reduction in vulnerability, which is commonly defined as the degree to which systems are likely to experience harm due to the exposure to a hazard<sup>11</sup>.

Over the last decades, substantial disaster management and adaptation efforts took place on the local and regional level<sup>12,13</sup>. However, it remains a challenging task to assess whether these local efforts effectively reduced the vulnerability of people and assets to floods on a global level since the implementation of adaptation measures does not necessarily reduce impacts<sup>14</sup>. To assess the implementation and effectiveness of adaptation measures at the global scale, one can start from the assessment of individual cases or measures and try to find efficient ways to create a global overview (bottom-up approach)<sup>15</sup>. Alternatively, globally collected damage data can be used to derive vulnerability changes by comparing the reported impacts to estimated exposure (=potential maximal impact) accounting for changes in hazards and exposure (top-down approach)<sup>16–18</sup>. The advantage of bottom-up approaches is that they allow assessing the planning and implementation<sup>12,13,19</sup> as well as the effectiveness of individual measures<sup>20,21</sup>, but the generalization of the results to larger regional scales or their transfer to other regions may be difficult and the aggregation subject to reporting biases and gaps. For instance, recent meta-studies of documented adaptation measures in cases of consecutive floods and droughts occurring in the same area (paired events), showed that the enhancement of flood risk management strategies lowered impacts of events of smaller or similar magnitudes as the previous ones in most cases<sup>20,21</sup>. Nevertheless, consecutive

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floods are associated with an increase in post-traumatic stress symptoms and adverse long-term impacts on physiological health<sup>22</sup>.

By contrast, temporal changes in vulnerability have been derived from global damage and fatality data combined with simulated<sup>17,18,23</sup> or estimated<sup>16</sup> flood extents. While these top-down studies have a global scope, accounting also for adaptation measures that are not explicitly reported as such, and quantify the overall effectiveness, a detailed identification of the individual measures is usually impossible. Previous top-down analyses of vulnerability changes over the time periods 1960–2013<sup>18</sup>, 1980–2015<sup>16</sup>, 1980–2010<sup>23</sup> and 1990–2010<sup>17</sup> consistently found asset vulnerability to floods and flood mortality to have decreased over the respective periods. However, these decreases in vulnerability were mostly achieved prior to the year 2000 and it is not clear whether vulnerability reductions continued in the 21st century. Overall the studies indicate that the reductions in vulnerability have not been strong enough to efficiently decrease impacts. For 1980–2010, the reported asset damages still increased, mainly driven by increases in exposed assets, but regionally also due to changes in climate<sup>23</sup>.

In this work, we aim to enhance previous top-down approaches by the following advancements: I) We derive global vulnerability changes by comparing reported damages and losses to exposed assets and people on an event basis, while before the comparison was done on a nationally or regionally aggregated level (Methods). II) In addition to asset damages and fatalities, we assess vulnerabilities for human displacements. III) Instead of relying on simulated flood extents to estimate exposure, we use flooded areas derived from satellite imagery from the Global Flood Database (GFD, 913 events). IV) We particularly focus on the period 2000–2018 to assess whether previous reductions in vulnerability have continued in the current century. Therefore, we combine the flood footprints from the Global Flood Database (GFD, 913 events)<sup>24</sup>, with the global disaster impact database NatCatSERVICE from Munich Re<sup>25</sup> (792 matching events with asset damage and 800 events with matching fatalities), the open-access disaster database EM-DAT<sup>2</sup> (312 matching events with asset damage and 560 matching events with fatalities) and the Global Internal Displacement Dataset (GIDD) from the Internal Displacement Monitoring Center (IDMC) (327 matching events with human displacement)<sup>1</sup> following the FLODIS approach<sup>26</sup> (Supplementary Fig. S1, Supplementary Tables S1 and S2). Thereby, both Munich Re and EM-DAT report estimates of the total damages on physical assets (e.g., buildings, infrastructure, etc.) including insured and uninsured damages. As the GFD is based on the Global Active Archive of Large Flood Events provided by the Dartmouth Flood Observatory (DFO)<sup>27</sup>, vulnerabilities for fatalities can additionally be assessed for the full set of 913 observations. The main analysis is focussed on vulnerability estimates based on NatCatSERVICE and IDMC, while EM-DAT and DFO are analyzed to test the consistency of our findings across different impact databases (Methods). Additionally, we complement our main results based on the gridded population of the world version 4 (GPW) dataset<sup>28</sup> by vulnerability estimates based on the population data from the Global Human Settlement Layer (GHSL)<sup>29</sup> (Methods). The restriction to flooded areas derived from satellite imagery makes our assessment independent of potential biases in modeled floodplains that often suffer from insufficient knowledge about protection measures limiting flood extents<sup>17,23</sup>.

Besides the assessment of past temporal trends, a better understanding of the determinants of vulnerability may provide insights into the future potential for vulnerability reductions. Even if temporal trends in vulnerability are minor, observing steep gradients of vulnerability with respect to a specific indicator can indicate a significant potential for vulnerability reductions. In addition, a better understanding of relevant drivers of vulnerability reduction may help to identify adaptation opportunities or to target adaptation action. To identify these potential gradients, we test a wide range of proposed indicators. While socio-economic development and income have been shown to be relevant predictors at the global scale<sup>17,30</sup>, studies conducted from a bottom-up perspective also indicate that governance-related factors, beyond solely considering GDP per capita, may play a crucial role in establishing the preconditions for enhancing adaptive capacity and building resilience<sup>31–34</sup>. A recent study on the relationship

between inequality and flood vulnerability found that in more inequitable countries floods kill significantly more people<sup>35</sup>. This relationship may be caused by a notable exposure bias of marginalized groups<sup>36</sup>.

In addition, aggregated disaster experience on the local, national or regional level is likely to create learning opportunities and may trigger flood management interventions that allow a better flood adaptation over time<sup>19,37,38</sup>. However, there are also studies that find only limited or no influence of disaster experience on adaptation action<sup>31,39</sup>. Major disasters and their impacts may overstrain communities, setting priorities to recovery and leaving policy makers unable to address future risk management<sup>31,39,40</sup>. Besides, adaptation in response to experienced impacts may be adequate to cope with the observed intensity of hazards, but may be insufficient if hazards continue to intensify<sup>20,21</sup>.

To cover the suggested determinants, we test three classes of factors influencing vulnerability levels: i) Socio-economic development (GDP per capita, the Human Development Index<sup>41</sup> and the GINI index<sup>42</sup> of the country where the reported event occurred and of the affected area), ii) flood experience (modeled indicator for population exposed<sup>43</sup> of the country where the reported event occurred), and iii) local structural characteristics that may be linked to the quality of local governance and flood management (availability of educational institutions, the Critical Infrastructure Spatial Index<sup>44</sup>, forest cover<sup>45</sup> and flood protection standards from FLOPROS<sup>46</sup>).

## Results

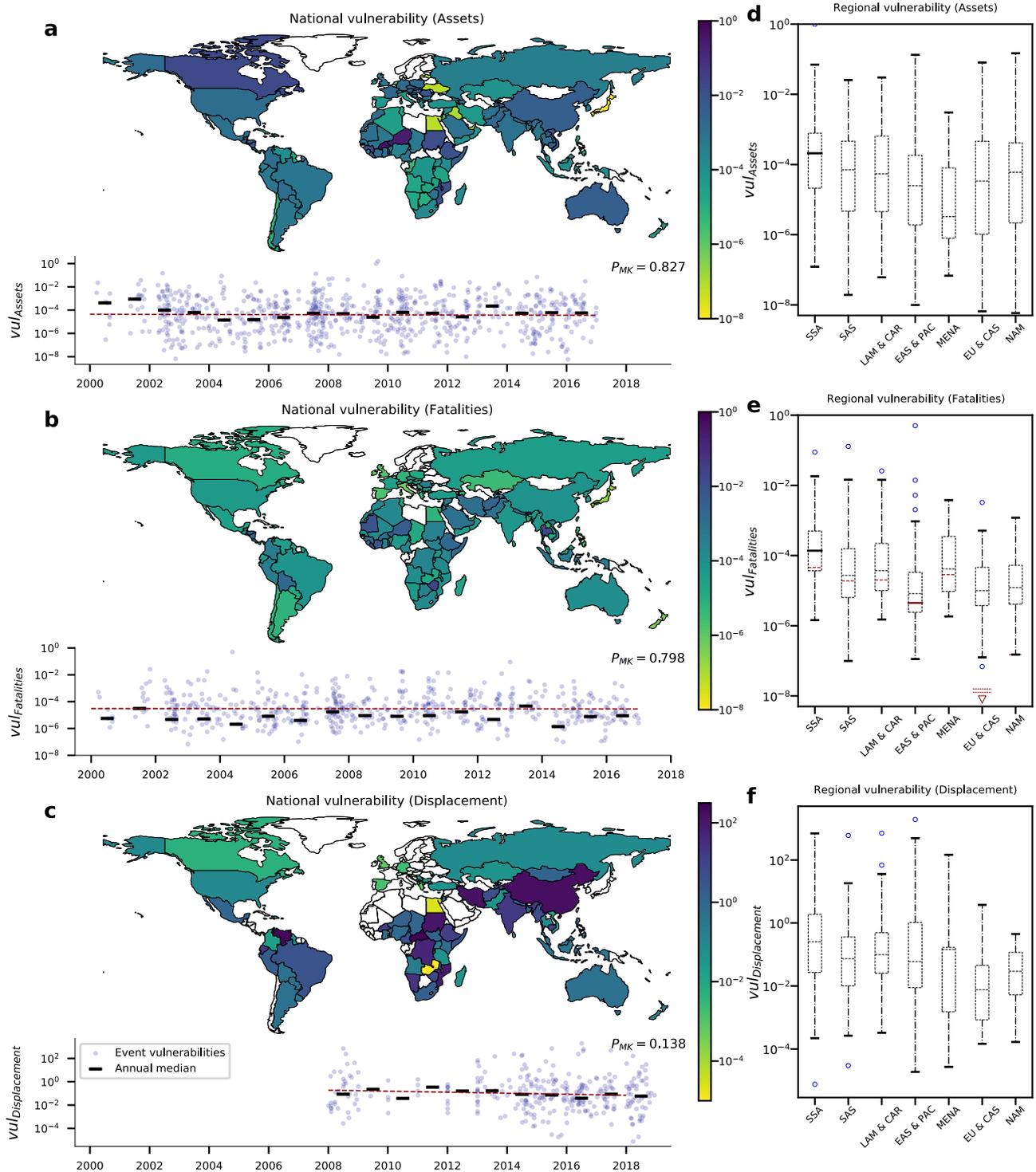
### Stagnation of flood vulnerability reduction since the beginning of the 21st century

We find that temporal trends in vulnerabilities are minor and insignificant for all three vulnerability categories over the observational periods (2000–2016 for asset vulnerability and mortality and 2008–2018 for displacements) (Fig. 1, Supplementary Table S1). Analyses with EM-DAT (asset vulnerabilities and mortalities) and DFO (mortalities) for the period 2000–2018 as well as results based on GHSL mostly confirm the absence of vulnerability reductions in the beginning of the 21st century (Supplementary Discussion, Supplementary Figs. S3–S5). Furthermore, we do not find any significant vulnerability reductions on the level of world regions<sup>47</sup> (Supplementary Figs. S2, S6, and S7, Supplementary Tables S4 and S5). Our analysis excludes observed events that do not appear in the NatCatSERVICE or IDMC database, as the reasons for the mismatch are unclear and probably diverse (Supplementary Discussion). Zero-vulnerability events represent a special case as they do not reflect varying exposure anymore (zero vulnerability no matter how large exposure was). For fatalities these events also occur among the matches between the observed flood events and the NatCatSERVICE or DFO data. However, including these events in our trend analysis, we do not find significant decreases in vulnerability either (Fig. 1 and Supplementary Table S3). As a robustness check, we introduce additional measures to account for changes in the frequency of occurrence and the exposure to zero-vulnerability events, which do not indicate a vulnerability reduction over time (Methods, Supplementary Discussion, Supplementary Figs. S8–S14).

### Vulnerability levels decrease with income and development

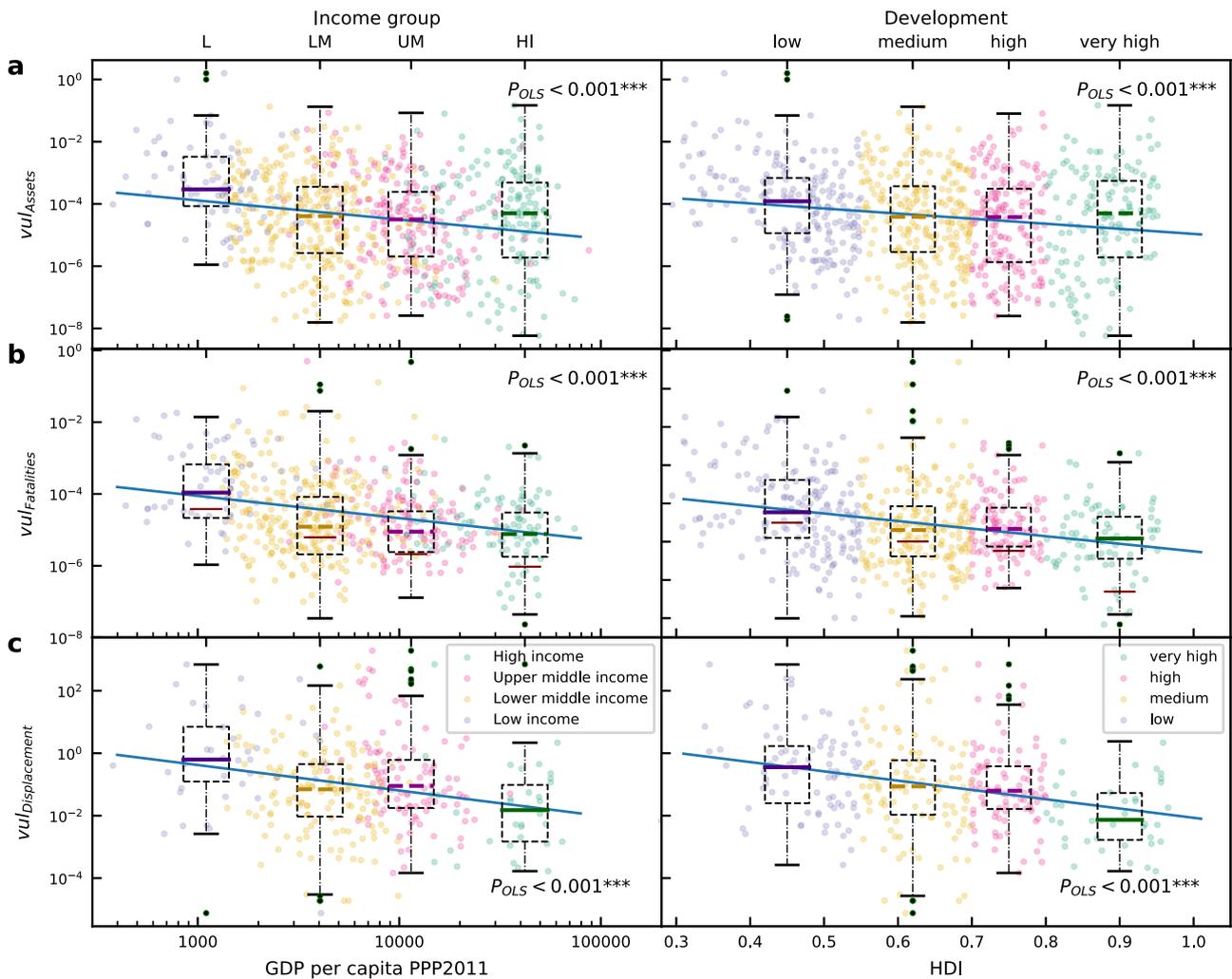
In general, there are only moderate differences in asset vulnerabilities among world regions, with the exception of Sub-Saharan Africa (SSA), which has a substantially higher asset vulnerability than all other regions (Fig. 1a, d). Egypt, United Arab Emirates, Lebanon, and Iraq in the Middle East and North-Africa (MENA) region and Ukraine and Latvia in Eastern Europe (EU & CAS) stand out with comparatively low asset vulnerabilities (Fig. 1a). Several highly developed countries such as Japan in EAS & PAC, Canada in North America (NAM), Australia in the Pacific (EAS & PAC) region, and most countries in Western Europe, except the Netherlands, show relatively high asset vulnerabilities as well (Fig. 1a).

In contrast, the mortalities in the high income regions (NAM), Europe and Central Asia (EU & CAS) along with the flood prone countries in Eastern Asia and the Pacific (EAS & PAC) are significantly lower than in Latin America & Caribbean (LAM & CAR), MENA, South Asia (SAS) and



**Fig. 1 | National and regional vulnerabilities for assets, fatalities and displacement.** **a** Map: National asset vulnerabilities (country medians). Time series: Event-based asset vulnerabilities with annual medians and trend line of the Ordinary Least Squares Regression (OLS) (red line),  $P_{MK}$  denotes the p-value of the temporal trend derived from a non-parametric Mann–Kendall–Test:  $P < 0.05^*$ ,  $P < 0.01^{**}$  and  $P < 0.001^{***}$ . Vulnerability estimates are based on the impacts given in NatCatSERVICE. **b** Same as **a** but for mortalities. Events without fatalities are not included in the visualization and the OLS-Regression, but are integrated in the Mann–Kendall-Test. **c** Same as **a** but for displacement vulnerabilities. **d** Boxplot for regional asset vulnerabilities in the logarithmic space sorted by their average GDP per capita. The definitions of the regions including Sub-Saharan Africa (SSA), South

Asia (SAS), Latin America & Caribbean (LAM & CAR), East Asia & Pacific (EAS & PAC), Middle East & North Africa (ME & NAF), Europe & Central Asia (EU & CAS) and North America (NAM) are given in Supplementary Fig. S4. Lines in the middle of the box mark the median. The boxes mark the inner quartiles of the data. **e** Same as **d** for mortalities. The brown horizontal bars mark the median vulnerability of the group when these events are included in the analysis. The brown dots for EU & CAS indicate that the median event in this region does not count any fatalities. **f** Same as **d** but for displacement vulnerabilities. Vulnerability estimates are based on the impact records from NatCatSERVICE and GIDD.



**Fig. 2 | Vulnerabilities at different levels of income and development.** **a** Event-level asset vulnerabilities (full line-significant or dashed line-insignificant) in dependence of GDP per capita adjusted to USD PPP 2011 levels and HDI levels. Dots show event vulnerabilities, and colors indicate the corresponding income group of the affected country. Boxes show the distribution of all event vulnerabilities including the median line. The boxes mark the inner quartiles of the data. Full median lines indicate a significant difference between the group and all others, while

dashed lines mark insignificant differences. P denotes the p-value of the OLS regression of asset vulnerabilities and GDP per capita and HDI:  $P < 0.05^*$ ,  $P < 0.01^{**}$  and  $P < 0.001^{***}$ . **b** Same as **a** but for mortalities. Brown horizontal bars indicate the median adjusted for the events without fatalities. Full lines mark a significant difference to other groups. Dashed lines show insignificant differences. **c** Same as **a** but for displacement vulnerabilities.

SSA (Fig. 1b, e). Notably, mortality in SSA is the highest among all regions. We observe pronounced regional variations in displacement vulnerabilities (Fig. 1c). SSA again shows a high level of vulnerability, which is however only insignificantly higher than in LAM & CAR and MENA (Fig. 1f). EU & CAS stand out due to their comparably low displacement vulnerability, mostly driven by European countries rather than Central Asian countries (Fig. 1c). Notably, other high income regions and countries, such as NAM and Australia, are significantly more vulnerable for displacements than EU & CAS.

Considerable differences in flood mortality and displacement vulnerabilities between regions suggest a vulnerability dependency on income and development. In general, there is a decrease of vulnerabilities with rising income across all three impact categories (Fig. 2). Grouping events according to Gross-national income per capita (GNIPc) of the country of occurrence into four categories (low income <USD 1058 GNIPc, lower middle income = USD 1086–4255 GNIPc, upper middle income = USD 2456–13,205 GNIPc, and high income > USD 13,205 GDPpc) according to the World Bank’s classification (Methods, Supplementary Table S6)<sup>47</sup>, we find significantly higher vulnerability levels at low income and development levels, while asset vulnerability levels only slightly decrease once middle

income and development levels are reached (Fig. 2a). Notably, we find the lowest asset vulnerability levels at the transition from upper-middle to high income levels and a considerable increase in vulnerability beyond 12,000 USD. This leads to a higher median vulnerability of high income countries compared to middle income countries. Differences in asset vulnerability between high income and both middle income groups, however, are insignificant.

Additionally, development levels (low, medium, high, and very high developed) are assigned to each event according to the average Human Development Index (HDI)<sup>48</sup> (Methods). Similarly to income levels, we find the highest vulnerabilities in low developed areas and a slightly higher median vulnerability of very high developed areas than of high developed areas, though this increase in vulnerability is insignificant. This is in line with previous studies on vulnerability that suggest increasing asset vulnerability at very high income levels<sup>17</sup>. The increase of vulnerability at high levels of income or development may result from biases introduced due to more comprehensive reporting in highly developed areas. On the other hand, the safety provided by higher protection standards may result in more people settling and more assets being built in flood-prone areas which results in comparably higher losses when the flood breaches the protection

infrastructures (levee effect)<sup>49,50</sup>. All in all, these results suggest only a weak dependency of asset vulnerability on income and development. This is supported by the absence of significant changes in asset vulnerability levels with higher income or development in EM-DAT (Supplementary Fig. S12, Supplementary Notes).

We observe a comparably stronger decrease in mortalities at higher income and development levels. Though the vulnerability decrease between middle income and high income levels is insignificant, vulnerability decreases significantly when moving from high to very high developed areas (Fig. 2b). While the increased mortality at low income and development levels is widely robust for EM-DAT and DFO comparisons, the significant decrease in mortality at very high development levels is limited to the NatCatSERVICE assessment (Supplementary Figs. S15–S17). The share of events without fatalities is significantly higher in countries and areas at higher socio-economic development levels (Supplementary Figs. S9d and S11c), however, taking into account the higher exposure in less developed countries or areas, suggests insignificant overall effects of events without fatalities on the differences in mortalities between income and development groups (Supplementary Figs. S8 b, S10b, and S14b).

Analyzing the dependence of displacement vulnerabilities on income and development, we observe a significant drop in vulnerability between low and medium income and development levels. Furthermore, vulnerability also decreases significantly at income levels higher than 20,000 USD and HDIs above 0.85 (Fig. 2c). Therefore, the vulnerability reduction with increasing socio-economic development is most pronounced for displacement vulnerabilities.

In summary, we find that there is a continuous decrease in displacement vulnerabilities with income and development. For displacement vulnerabilities, the decrease at high income and very high development levels is more pronounced than for mortalities. However, significant reductions of asset vulnerabilities due to improvements in socio-economic development (i.e., increases in income and development) are only relevant at low levels of socio-economic development. Given that socio-economic development has progressed over the study periods (Supplementary Figs. S18 and S19), its effect on vulnerability levels, though significant, is limited in magnitude, as the moderate increases in socio-economic development over the observation period do not induce significant downward trends in vulnerability. An analysis of vulnerability changes over time does not reveal any significant robust temporal decrease of vulnerabilities in any of the income groups either (Supplementary Notes, Supplementary Figs. S20 and S21, Supplementary Tables S7 and S8).

We further test the dependence of vulnerability levels upon national inequality measured by the national GINI index (Fig. 3 and Supplementary Fig. S22). A recent study by Lindersson et al.<sup>36</sup> has shown that impacts can increase with higher inequality, e.g. due to an increased exposure of marginalized groups<sup>36</sup>. In this case, comparing the impact with exposure as in our vulnerability metric could partially conceal or even invert inequality effects on flood impacts. To test this, we additionally consider the damage, and the numbers of fatalities and displacements for each flood (Supplementary Fig. S23). Globally, the relationship between asset vulnerabilities and inequality is insignificant (Fig. 3a). While we observe a significant decrease in asset vulnerabilities with increasing inequality in high income countries, the correlations within other income groups are insignificant. Regarding the impact, we find significant reductions of asset damages per flood event with increasing inequality for high and middle income countries (Supplementary Fig. S23a). These results suggest that in countries with higher inequality the share of monetarily less valuable exposed assets increases, which reduces the overall impacts. Thus, the significant reduction of asset vulnerability with increasing inequality in high income countries could partially result from a reduction of the impact due to a higher vulnerability of monetarily less valuable assets.

There is a significant reduction in flood mortalities with decreasing levels of inequality at global level (Fig. 3b). This relationship is driven by the middle income groups, showing significantly lower vulnerabilities in more equal countries. By contrast, low income countries show higher mortality

levels at lower levels of inequality. We find a strong significant increase in the number of fatalities per flood event with rising inequality at the global level, which is predominantly driven by the strong increase of fatalities with inequality in high-income countries and, to a smaller degree, in higher-middle income countries (Supplementary Fig. S23b). This suggests that the global increase in mortality with inequality in high and higher middle income countries may indeed be driven by an increase in the exposure of more vulnerable groups. By contrast, the reduction of vulnerability with rising inequality in low income countries could be (partially) driven by a reduction of the impact, due to a better protection of people from less vulnerable groups.

Displacement vulnerabilities significantly increase with higher inequality at the global level. However, this relationship appears to be not very robust since none of the income group regressions is significant. Thus, the global trend may result from a negative correlation of the GINI index with income (Fig. 3c). The number of displacements per flood is uncorrelated with inequality on the global level. However, there is a significant increase of displacements with higher inequality in low income countries and a significant decrease of displacements per flood with higher inequality in middle-income countries. Thus, it is not clear whether the global increase in displacement vulnerabilities with increasing inequality is driven by an unequal exposure.

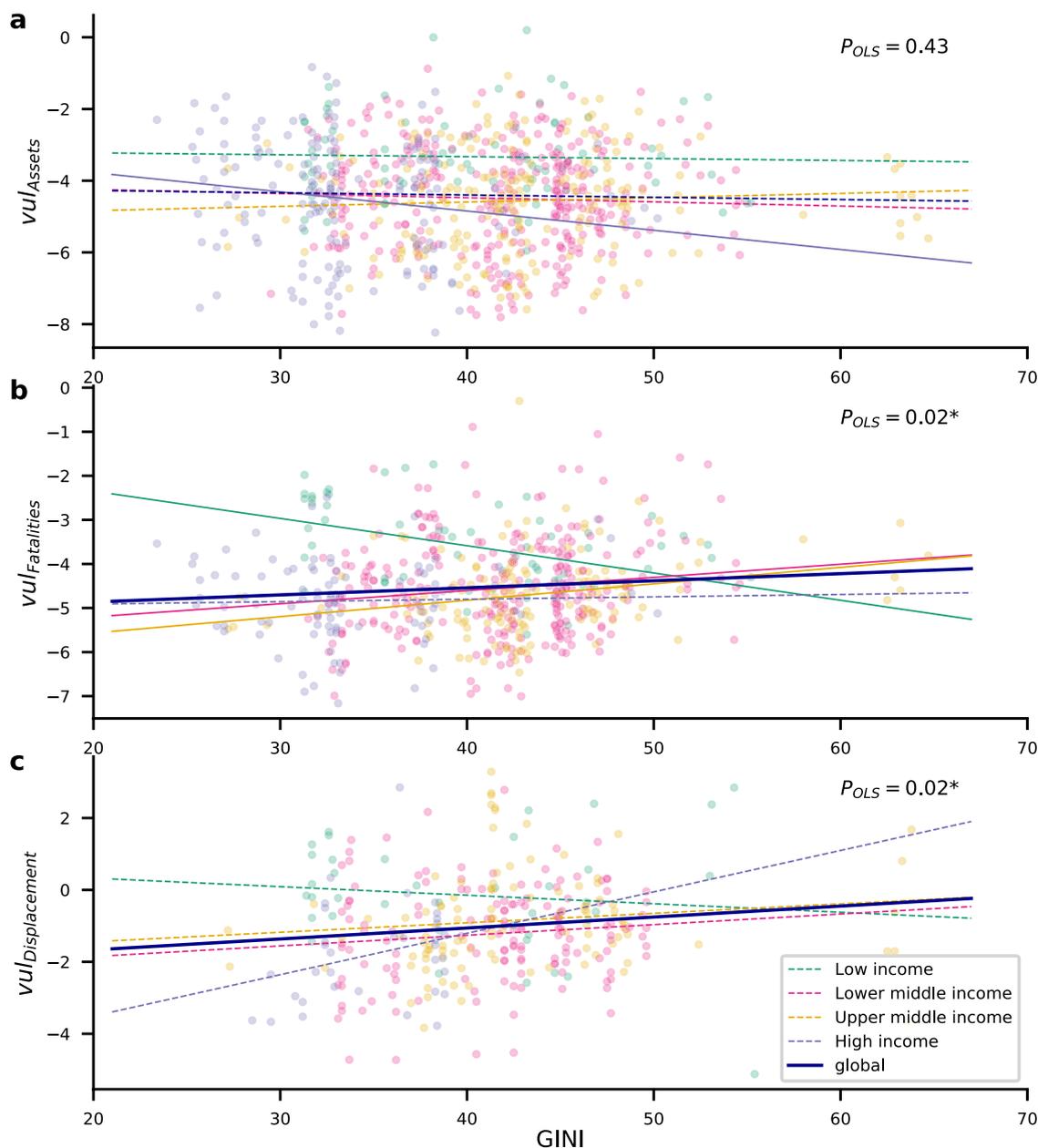
### The effect of historical flood exposure on vulnerability reduction is limited

To assess the relationship between the physical flood risk of countries and their vulnerability levels, we use country-level hypothetical flood exposure (national share of population) from flood risk simulations assuming no protection measures<sup>43</sup> as a proxy for the historical and current relevance of floods in a country (Methods).

Hypothetical flood exposure is highest in the Netherlands, the entire South and East Asian region, and Egypt (Fig. 4a). We find that increased flood exposure does not correlate with a notable reduction in asset vulnerability (Fig. 4b), while there is a pronounced vulnerability reduction in mortality in terms of higher flood exposure (Fig. 4c) and a weaker—but still significant—reduction in displacement vulnerability with increasing flood exposure. The decrease of displacement vulnerability is mostly driven by the highly flood-exposed countries of Vietnam and Bangladesh (Supplementary Fig. S26); for less exposed countries (less than 30% of the population exposed), the decreasing trend in displacement vulnerability is insignificant (Fig. 4d). The decrease in mortality with increasing flood exposure is mostly driven by low- and lower-middle income countries and weakens at higher income levels (Fig. 4c). Results derived from EM-DAT or GHSL confirm the significant mortality reduction with increasing flood exposure as well as the absence of effects of flood exposure on asset vulnerability (Supplementary Figs. S27 and S28, Supplementary Notes).

### Better structural properties related to good governance reduce vulnerabilities significantly

Higher quality of governance measured by levels of CISI and educational institutions reduce vulnerability levels significantly (Fig. 5, Supplementary Figs. S29, S32, and S33), while higher forest cover is associated with slightly lower levels of asset vulnerability and mortality, but is an insignificant factor for displacement vulnerabilities (Supplementary Fig. S30). Higher physical flood protection levels indicated in the FLOPROS database significantly reduce vulnerabilities across all impact categories (Supplementary Fig. S31). However, the FLOPROS data is only partly based on empirical information, as only for a small share of provinces the implemented protection level is known<sup>46</sup>. Protection standards are therefore mostly modeled in dependence of province-level per-capita GDP. Consequently, they are strongly correlated with per-capita GDP (Spearman-rank correlation coefficient  $r_S = 0.58$ ) and the additional explanatory power contributed by this indicator is at least limited. This assumption is strengthened by the finding that within income groups a significant correlation of higher FLOPROS with lower vulnerability is largely absent (Supplementary Fig. S31). The structural indicators are not



**Fig. 3 | Event-level vulnerabilities in relation to national inequality.** **a** Event-specific asset vulnerabilities in relation to the national GINI index. **b** Same as **a** but for mortalities. **c** Same as **a** but for displacement vulnerabilities. Blue trend lines indicate the slope of the linear regression of vulnerabilities and the GINI index and

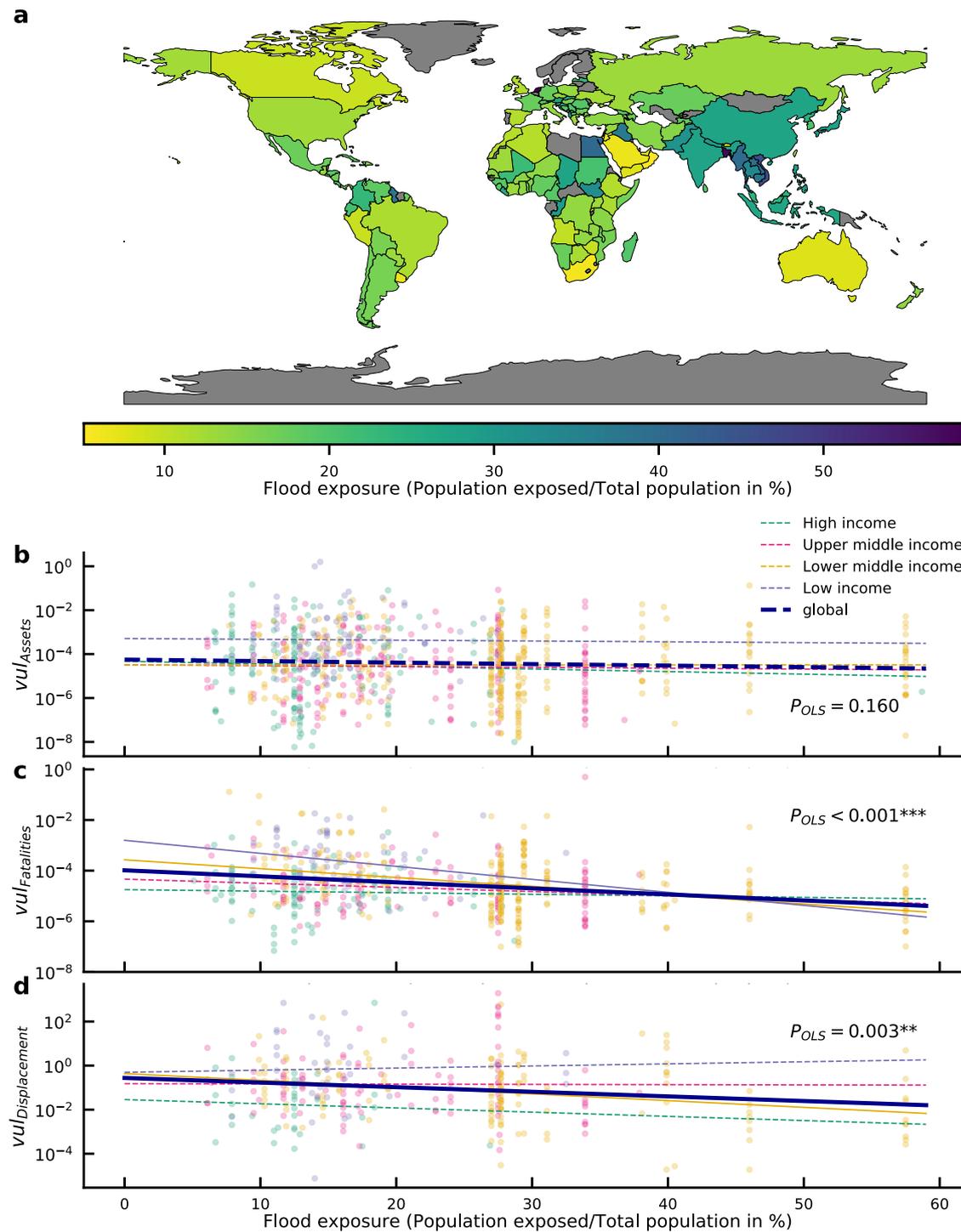
its significance (full line indicates significance at 5% level). *P* denotes the corresponding *p*-value:  $P < 0.05^*$ ,  $P < 0.01^{**}$ , and  $P < 0.001^{***}$ . Trendlines in other colors denote trends and significance of the relationships between vulnerabilities and inequality in the corresponding income group.

independent of socio-economic development, but the reduction of vulnerabilities with increasing CISI, or in the case of asset vulnerabilities increasing availability of educational institutions, remains significant within different income groups (at least three out of four) (Fig. 5 and Supplementary Fig. S29). There are notable regional differences in the relevance of the CISI indicator for vulnerability reduction (Supplementary Fig. S34). While the relationship is very pronounced across all vulnerability categories in EAS & PAC, LAM & CAR and SEA, it is less robust in EUR & CAS, NAM and SSA. For forest cover and FLOPROS, the limited overall reduction in vulnerabilities is either driven by only one income group or is a result of the correlation with GDP per capita (Supplementary Figs. S12 and S14). Notably, for both assets and fatalities, the vulnerability reduction with improved CISI is significantly less pronounced in low income countries than in other income groups (Fig. 5).

**Performance of socio-economic development, flood exposure, and structural characteristics as predictors of vulnerabilities**

Overall the structural characteristics (availability of educational institutions and critical infrastructure) have the largest explanatory power for the observed vulnerability variations (Table 1). Mortalities and displacement vulnerabilities can be best explained by availability of critical infrastructure with  $R^2$  reaching more than 20%, while the access to educational institutions has the highest individual explanatory power for the vulnerability of assets only reaching 5.5%.

Although structural characteristics are correlated with the socio-economic development indicators (GDP per capita or HDI) they contribute relevant explanatory power for vulnerability levels that cannot be derived from socio-economic development (Table 1a, Fig. 6). On a global level,



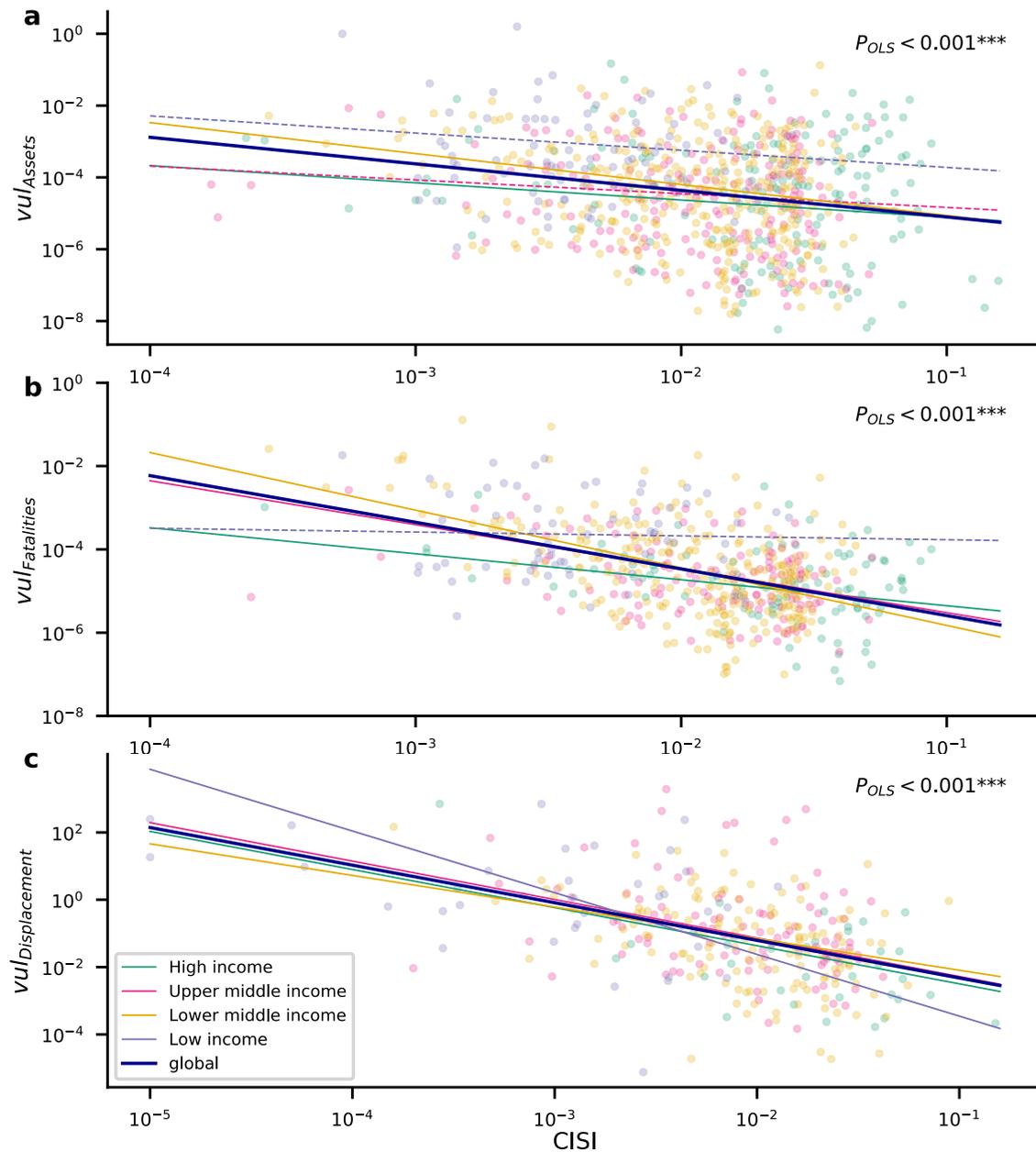
**Fig. 4 | Event-level vulnerability in relation to national flood exposure.** **a** Flood exposure as the share of total national population hypothetically exposed to flooding assuming no physical flood protection according to Rentschler et al.<sup>43</sup> **b** Event-level asset vulnerability in relation to the flood risk of the country. Blue trend lines mark the slope and the significance (at the 5% level) of the linear regression of asset

vulnerabilities and flood exposure and its significance (full line indicates significance at 5% level).  $P$  denotes the corresponding  $p$ -value:  $P < 0.05^*$ ,  $P < 0.01^{**}$  and  $P < 0.001^{***}$ . **c** Same as **b** for fatalities. **d** Same as **b** but for displacement. Country-level vulnerabilities in dependence of the national flood exposure are given in Supplementary Fig. S26.

inequality has very limited explanatory power for event vulnerabilities (Table 1), due to the strong differences between income groups. Combining both types of predictors (Table 1b and Supplementary Table S9) leads only to small improvements in explanatory power compared to the best individual structural predictor across all impact categories. The multivariate regression confirms that flood exposure provides some explanatory power for mortalities, as the explanatory power increases to 27% when the

predictor is added. Similarly, it shows that asset vulnerabilities are independent of flood exposure, while it confirms the assumption that the reduction of displacement vulnerabilities with increasing flood exposure is not robust, as models for asset and displacement models are barely improved through adding flood exposure (Table 1c).

When allowing for non-linear relationships between the predictors and vulnerabilities by applying a Random Forest Regression (Methods,



**Fig. 5 | Event-level vulnerabilities in dependence of available critical infrastructure.** **a** Event-specific asset vulnerabilities in dependence of the Critical Infrastructure Spatial Index (CISI) in the flooded area. Blue trend lines indicate the slope of the linear regression of asset vulnerabilities and CISI and its significance (full

line indicates significance at 5% level). *P* denotes the corresponding *p*-value: *P* < 0.05\*, *P* < 0.01\*\* and *P* < 0.001\*\*\*. **b** Same as **a** but for mortalities. **c** Same as **a** but for displacement vulnerabilities.

Supplementary Table S10), the explanatory power for asset vulnerability can be increased to 14% and 38% for mortalities but does not change for vulnerability to displacement. However, the general pattern that asset vulnerability is less well explained than mortality and displacement vulnerability, while mortalities can be best explained is preserved, as well as the relevance of flood exposure for flood mortalities.

The individual relevance of structural characteristics for explaining mortalities and displacement is confirmed by EM-DAT and DFO, but for asset vulnerabilities only by DFO (Supplementary Figs. S33 and S36). For flood mortality, the relevance of the tested determinants for vulnerability remains unchanged if the effects of events without fatalities are assessed preserving differences in exposure (Supplementary Discussion, Supplementary Figs. S8, S10, and S14 and Supplementary Table S11).

### Discussion

Our analysis of temporal changes of the vulnerabilities of exposed assets and exposed people (in terms of mortality and displacement) to floods over the first 18 years of the 21st century shows that vulnerability reduction has stagnated after strong reductions detected in the decades before<sup>16-18</sup>. This finding is robust across the three impact categories (assets, fatalities and human displacement) and across the four income groups and all world regions. The lack of progress in reducing vulnerability observed in the period following the year 2000 suggests that there may be inherent limitations to further decreasing vulnerability. Nevertheless, our analysis clearly shows that lower vulnerability levels are linked to structural properties, indicating further potential for adaptation through vulnerability reduction. Regarding the data on human displacement, the lack of discrimination between planned evacuation and involuntary displacement complicates the

**Table 1 | Relative importance of the three different classes of vulnerability determinants (socio-economic development, flood experience, and structural characteristics) as vulnerability predictors**

	vul <sub>Assets</sub>			vul <sub>Fatalities</sub>			vul <sub>Displacement</sub>		
	a	b	c	a	b	c	a	b	c
Socio-economic development									
GDP per capita	3.5%	X	X	7.0%		X	4.8%		
HDI	2.3%			7.1%	X		7.8%	X	X
GINI	0.3%			0.4%			0.5%		
Flood exposure	<0.1%		X	5.3%		X	1.5%		X
Structural characteristics									
Educational Institutions	5.5%	X	X	15.6%			3.3%		
Forest cover	1.9%			0.4%			0.4%		
Critical Infrastructure	4.6%			21.8%	X	X	20.6%	X	X
FLOPROS	1.4%			8.5%			5.5%		
Multivariate regression	–	6.3%	7.0%	–	22.7%	26.9%	–	22.2%	22.8%
Random Forest Regressor	–	13.6%	14.0%	–	26.3%	37.6%	–	19.2%	21.9%

a The explained variance (R<sup>2</sup>) (out-of-sample) of vulnerabilities achieved with each single indicator given in the first column. b Bivariate regression model including the best combination of a socio-economic predictor (GDP per capita or HDI, GINI) and a structural predictor (availability of critical infrastructure (CIS) or educational institutions). Crosses indicate the predictors included in the model. The last two rows indicate the R<sup>2</sup> (out-of-sample) of the multivariate regression and the Random Forest Regressor. c Multivariate regression model extending the previous model by flood exposure. Crosses indicate the predictors included in the model. The last two rows indicate the R<sup>2</sup> of the multivariate regression and the Random Forest Regressor (out-of-sample prediction).

interpretation of our findings: the absence of a significant vulnerability reduction over time could be a sign of missing adaptation and poor flood management, but high displacement rates may also be an indicator for effective evacuation policies.

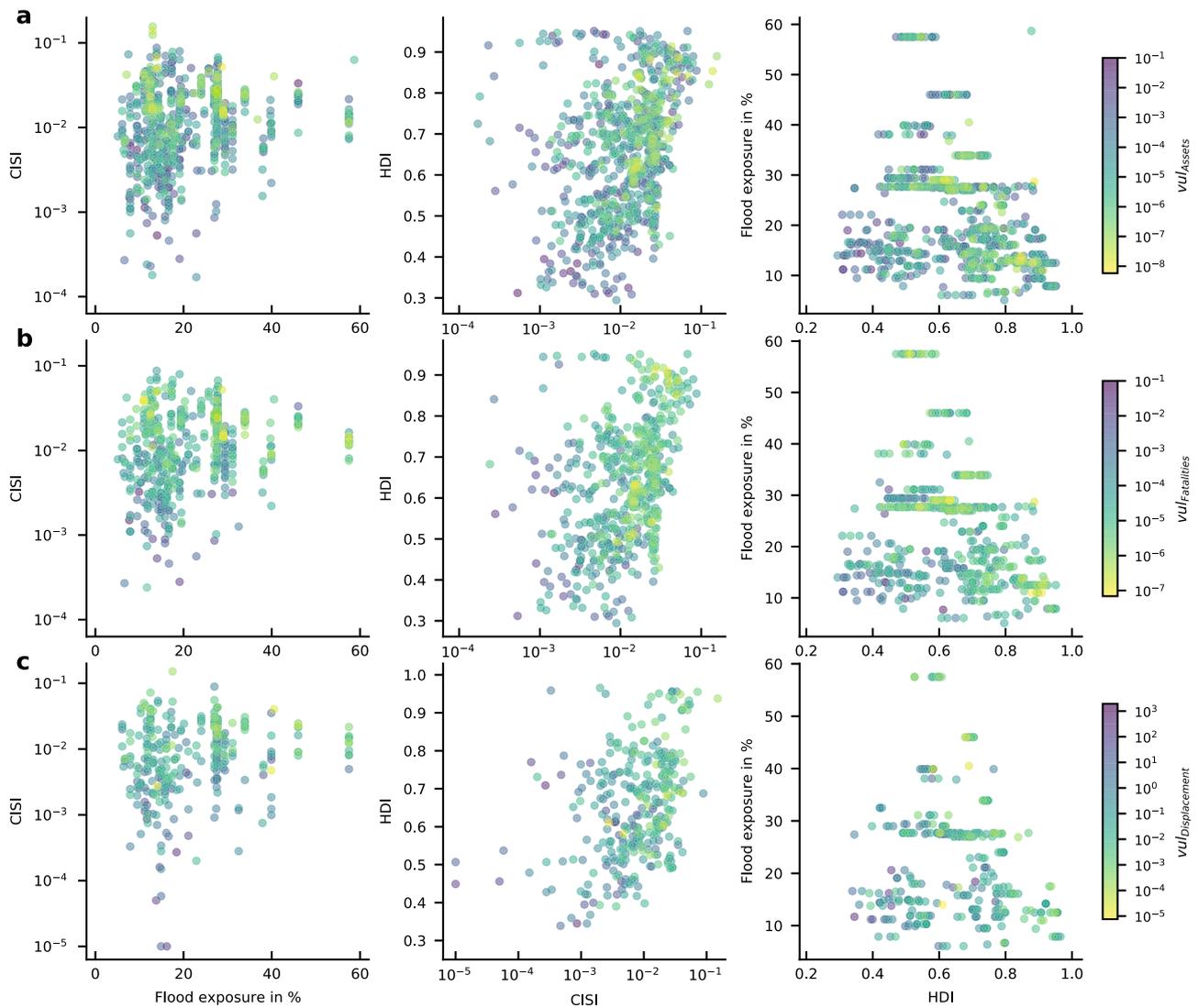
We further assess three classes of potential drivers of vulnerability reductions. In line with earlier vulnerability studies, we find that higher income and development reduce vulnerabilities. However, especially for asset vulnerabilities, we find significant vulnerability decreases with socioeconomic development only at low income and HDI levels. This suggests that socio-economic development becomes less important as a driver of vulnerability reductions at higher levels of socio-economic development. This is partially in line with an early study by Jongman et al.<sup>17</sup> showing that vulnerability levels between low- and high-income countries converge. In our analysis for the early 21st century, evidence for an ongoing catch-up process of lower-income areas is missing as vulnerability changes are minor and insignificant at all income levels (Supplementary Figs. S20 and S21). Further, our analysis shows that, in the first 18 years of the 21st century, socio-economic development was too weak as a driver of vulnerability reductions to further decrease vulnerability levels globally. The dependence of vulnerabilities upon socio-economic development is most pronounced for displacements. In highly developed areas it may be even more likely that people were not forced to leave their livelihoods due to experienced impacts, but were evacuated as a precaution. This underlines the unequal risk distribution for involuntary displacement due to floods globally.

Intuitively one would expect that asset and displacement vulnerability as well as mortality are correlated because more robust assets may also protect people. Comparing regional differences in flood vulnerability across the different impact categories, this is partly confirmed, as we find that EAS & PAC as well as EU & CAS are among the least vulnerable regions across all impact categories. In contrast, SSA is the most vulnerable region independent of the impact indicator. However, vulnerability levels differ strongly between impact categories in MENA and NAM. While MENA is least vulnerable for asset damage, but has comparably high flood mortalities and displacement vulnerabilities, NAM has high asset vulnerabilities and is less vulnerable for fatalities and displacement (Fig. 1d–f). These differences in vulnerabilities between impact categories may be related to different management priorities and building standards or policies in MENA and NAM. While the result suggests higher building standards in the MENA region, they imply a better protection of human life in NAM. However, especially in

the MENA region the number of observations is too small to draw these conclusions with confidence.

We do not find significant correlations between inequality and asset vulnerabilities, except for high income countries where vulnerability decreases with rising inequality. However, since we here define vulnerability as the ratio of impact (reported damage) and exposure (exposed physical assets), this result deserves some more contextualization. In unequal high income countries the asset exposure in a given grid-cell is dominated by the valuable assets, which are likely to be protected and robust. In contrast, the impact may be dominated by the unprotected, less valuable and more exposed assets in poorer areas. This could explain why the overall asset vulnerability is lower in areas with higher inequality. This finding stresses the limitations of the asset damage indicator for the assessment of distributional effects, as more livelihoods may be destroyed in regions where asset vulnerability appears to be lower. Flood mortalities significantly decrease with increasing equality, in particular in the middle income countries. Since our vulnerability metrics do not allow us to decide whether changes in vulnerability with inequality are driven by changes in impact or exposure, we additionally investigate the mere impacts in terms of absolute fatalities and displacements per flood. In line with a study of Lindersson et al.<sup>35</sup>, we find that the number of fatalities per flood increases with higher inequality in high and higher middle income countries while it decreases in low and middle income countries. These diverging effects of inequality across different income groups may be rooted in the different types of poverty found in these country groups. In unequal high and higher middle income countries, the comparably high impacts may be a result of power asymmetries and exposure biases due to spatial marginalization. By contrast, in more equal low income countries, they may result from absolute poverty impeding effective disaster risk management and disaster protection, while in low income countries with high inequality at least very small parts of the societies may be able to afford protection measures.

The influence of national flood exposure on vulnerabilities is strongly dependent on the impact category. While flood exposure has some effect on mortalities, asset vulnerabilities are unrelated to flood exposure in all respects. The differences may be rooted in the faster and easier implementation of soft measures, such as early warning-systems and evacuation plans that are suitable to protect people, but not their assets. Notably, the decreasing trends in mortality with increasing flood exposure are stronger at lower income levels. The effect of flood exposure may be stronger in low income areas as their general mortality levels are higher, so more basic



**Fig. 6 | Relationship between vulnerability and development, flood exposure and availability of critical infrastructure.** **a** Event-level asset vulnerabilities in dependence of flood risk as share of exposed population in % (HDI), of development level and of implemented critical infrastructure (CISI). **b** same as **a**, but for mortality. **c** same **a** row, but for displacement vulnerability.

measures may be already helpful to reduce mortalities. Additionally, flood exposure in high income countries has most likely been gained in earlier time periods, while today societies may rely on the effectiveness of existing infrastructure and awareness may be lower<sup>51,52</sup>. In low income areas, people may be more aware through recent exposure<sup>51</sup> with frequent floods with comparatively low intensities. Regarding exposure reduction, these experiences have been shown to be more effective for adaptation than rare high magnitude floods<sup>53</sup>. Previous flood exposure as a driver for reduction of flood mortality is particularly relevant, as there are areas in the world, such as North America, parts of Europe and East Asia, where flood exposure has decreased in the past, but will increase under climate change<sup>24</sup> and cause unprecedented flood events with potentially larger impacts<sup>20</sup>. In line with previous studies, we find that previous flood exposure does not uniformly reduce impacts if hazard and exposure increase<sup>20</sup>. Former studies found no or limited influence of disaster experience on disaster risk reduction and adaptation policies, but do not explicitly address actual risk reduction<sup>31,39</sup>. Our findings complement these studies showing that the effect of previous flood exposure on actual flood vulnerability is also limited, especially for asset and displacement vulnerabilities (Table 1).

Our research suggests that local structural characteristics are the most powerful predictors of vulnerability levels. Especially, higher availability of

critical infrastructure is associated with lower vulnerability levels. One reason that structurally strong areas have lower vulnerabilities may be that critical infrastructure availability is a proxy for protective infrastructure. For example, sophisticated health infrastructure may indicate a higher level of civil protection. Further, availability of critical infrastructure may be linked to good governance and thus effective flood responses. In the analysis, it stands out that the best explanatory variables for vulnerability (educational institutions, access to critical infrastructure) are closely related to urbanization. On the one hand, urbanization is often highlighted as a driver for increasing flood risk, basically through high exposure and sealed soils<sup>54,55</sup>. On the other hand, cities are important areas in terms of climate change adaptation mainstreaming and promoting of good governance<sup>56</sup>. Our study suggests that the latter aspect was potentially more important in the historical study period, as we find lower vulnerability levels in areas with improved structural characteristics. Therefore, we argue that the relevance of urbanization related indicators can be most likely rooted in improved governance and a more effective approach to adaptation in urban areas. However, there are several regions where vulnerability levels do not depend upon structural characteristics. For instance, in less developed Sub-Saharan African countries, areas with good structural characteristics are as vulnerable as remote areas with poor structural characteristics. This may be due to

informal settlements in urban floodplains with low availability of critical infrastructure. The ineffectiveness of structural development for vulnerability reduction in SSA may stress the need to support the ongoing settlement in flood safe areas<sup>43</sup> and to impede further urbanization of flood prone areas. Also in high income regions such as North America, Europe, and Central Asia structural development does not significantly reduce vulnerability across all impact categories. In these regions there has been little additional encroachment of flood prone areas in recent decades<sup>57</sup>. As these regions rely more strongly on hard infrastructure than lower income regions, impact reduction through structural development is mainly achieved through the containment of floodplains. This is, however, not represented by the vulnerability indicators used in this study. It would be therefore interesting to investigate in future work whether the containment of floodplains or legislation restricting urban development in floodplains have indeed effectively reduced impacts in high income regions by linking flood data with local and regional policies.

The absence of vulnerability reduction does not mean that no effective adaptation efforts have been undertaken between (2000–2018). Our method does not capture adaptation through exposure and hazard reductions. In spite of the limited relevance of the flood specific governance indicators such as forest cover and FLOPROS for vulnerability reduction, these indicators may rather reduce impacts by limiting the hazards through both flood protection standards such as dikes as well as permeable soils of river meadows or mangroves. Our study does not address impact reductions by reducing exposure, either. So far, global studies on the effect of exposure change on flood impact suggest that population in flood prone areas increased<sup>24</sup> and that increasing asset exposure in the last decades has been a main driver of increases in flood impacts<sup>23</sup>. However, the resolution of the datasets used for exposure estimation in these studies may be too coarse to detect small-scale changes in riverine floodplains and coastal areas. Mård et al.<sup>52</sup> studied adaptation through exposure reduction as a response to previous disaster experiences for a small selection of river basins. They observed a retreat from flood prone areas of populations lacking reliable protective infrastructure<sup>52</sup>. In contrast to our study, previous studies building on simulated instead of observed flooded areas implicitly include changes in hazards in their vulnerability assessments, as models always assume constant protection levels<sup>16–18</sup>. Nevertheless, these studies also outline a slow-down of the vulnerability decrease from 2000 onwards, suggesting that progress on adaptation through the limitation of flooded areas has also been limited over our observation period. However, further research is needed to quantify vulnerability reduction through exposure reduction globally.

As a global vulnerability assessment, our work is subject to a number of assumptions and limitations:

- i) *Representativeness of the event sample*: The flood events included in this study only represent a small portion of the overall flood events that took place between 2000 and 2018, which may raise concerns regarding the representativeness of the sample. The time period is relatively short to make statements on the temporal evolution of vulnerabilities, though regarding adaptation mainstreaming, the considered years are of critical relevance for climate action including adaptation goals<sup>58</sup>. We are able to match about 14% of the events (in NatCatSERVICE), so there remains a considerable amount of events that we do not capture, limiting the statistical representativeness of the sample. Nevertheless, we would consider our main finding on the absence of further vulnerability reductions in the early 21st century to be robust, because systematic underreporting of low-vulnerability events in later years of our observation period is rather unlikely, as we would expect that the quality of the reporting has improved over time. Further, impact databases are most likely biased due to an underreporting in less developed countries (Supplementary Fig. S1). It is likely that the overall number of flood events is underestimated as event numbers in Africa are strikingly low compared to other areas (Supplementary Fig. S1). Given that events with higher impacts are more likely to receive global attention, there might be a bias towards high vulnerability events in less

developed countries. This could lead to an overestimation of the effect of income and development on vulnerability levels through an overestimation of vulnerability in less developed countries.

- ii) *Neglect of physical flood drivers*: we only use flooded areas as a hazard indicator, neglecting that variations in physical characteristics, such as water level, flood duration and water velocity, modulate flood damage, fatalities, and displacement.
- iii) *Neglect of sociosanitary vulnerability characteristics*: Indicators such as accessibility to water and sanitation and hygiene infrastructure etc. can influence the vulnerability and recovery capacity of individuals and communities to disasters<sup>59,60</sup>.
- iv) *Definition of flood exposure*: In this study, we define flood exposure as the number of potentially exposed people in the absence of protection standards in order to reflect the historical flood experience of countries. In this way, we obtain an indicator that is constant throughout the observation period. Flood exposure is investigated as a national indicator, but learning from previous flood exposure may take place across other administrative levels. Local experience may be necessary to implement local protection measures<sup>13,61</sup>, while countries are also shown to even learn from experiences of their neighbors<sup>62</sup>. Additionally, the interaction with exposure to other hazards may be critical, as experiences from other disaster types may be helpful to reduce flood vulnerability or may shift the focus only to the hazard type that occurred most recently<sup>39</sup>. Most effective adaptation reduces event records, as in the case of Japan and the Netherlands, thus data on very low vulnerability events may be hidden as reporting thresholds are not exceeded.
- v) *Limited representation of flash floods*. As the GFD does not cover flash floods occurring at very small time scales, this vulnerability analysis does not cover these types of floods. This may be a severe limitation as this flood type often causes large impacts and may be particularly relevant for mortality assessments. Additionally, there is most likely a globally consistent underestimation of the flood extent for floods with fast moving water (Methods). This causes an underestimation of the exposure, thus an overestimation of vulnerability that most likely does not systematically affect the main results of this analysis.

Our work highlights that relying on vulnerability reductions with socio-economic development may be a risky strategy because the income increases of the last two decades were too moderate to significantly reduce vulnerability at the global level (Supplementary Figs. S18 and S19). Despite the apparent lack of progress in further vulnerability reduction, it is unlikely that the limits of adaptation have already been reached, as the strong dependence of vulnerability on governance related structural characteristics outlines further opportunities. The lack of vulnerability reduction over time found in this study may be partially rooted in higher demands on flood management for impact reduction due to growing exposure in flood prone areas<sup>24</sup>. Ongoing population expansion and urbanization trends show a strong increase of population in flood prone areas<sup>24,57,63</sup>. This suggests that some societies have actively amplified their flood risk over the last decades by not restricting urban development in floodplains<sup>63</sup>. Though urban areas benefit from a better structural development than rural areas, they often perceive larger impacts, especially in middle income regions (Supplementary Fig. S36). On the one hand, this stresses the importance of adaptation efforts in cities where impacts are disproportionately large. On the other hand, it is important to keep in mind that, according to our findings, (rural) areas with poor critical infrastructure have a higher vulnerability to floods than (urban) areas with well-developed infrastructure. Thus, adaptation efforts are needed in both remote, structurally underdeveloped areas as well as in urban, structurally well developed areas. In rural areas this may most effectively be achieved by vulnerability reduction (e.g., through adaptation mainstreaming) whereas in urban areas (where vulnerability is already comparably low) a reduction of exposure may be more efficient<sup>64</sup>. Ideally this is achieved through inequality sensitive adaptation measures accounting for potential exposure biases of marginalized groups<sup>36</sup>.

## Methods

### Flooded areas

As hazard indicators we used satellite-based observations of flooded areas as reported in the Global Flood Database (GFD, <http://global-flood-database.cloudtostreet.info/>). Based on the archive of the Dartmouth Flood Observatory (DFO), the database contains geospatial information on the maximum surface water extents of 913 flood events between 2000 and 2018, which were derived from NASA MODIS satellite sensors (<https://floodobservatory.colorado.edu>)<sup>24</sup>.

### Impact data

Observed asset damages were adopted from the NatCatSERVICE<sup>25</sup> database collected by Munich Re and from the International Disaster Database EM-DAT since the year 2000. For NatCatSERVICE, we selected all damages and fatalities recorded for events of the type *general flood*, *flash flood* and *storm surge*. For EM-DAT, we selected all events of the disaster type *flood*. This includes the disaster subtypes *riverine flood*, *flash flood* and *coastal flood*. For displacements, we used all records from the GIDD dataset provided by the International Displacement Center (IDMC) for the disaster type *flood*. As the GFD is based on the Global Active Archive of Large Flood Events provided by the Dartmouth Flood Observatory (DFO), the flooded areas are connected to the impacts recorded in this database. DFO includes the number of fatalities and displacements. However, due to the inconsistencies in the definition of the displacement indicator within DFO, including also affected people in some cases, in this work, we used only information on fatalities from DFO. As matches of EM-DAT and GFD are sparse, especially for asset damages (Supplementary Fig. S1 and Supplementary Table S1), and the DFO records do not systematically account for the impacts experienced in individual countries, which is a prerequisite for parts of the analysis, we used these databases to check the robustness of the results for asset vulnerability and mortality based on data from NatCatSERVICE.

To achieve comparability between recorded damage and exposed assets, damage records were converted to the same unit as exposed assets based on global GDP distribution provided in constant 2011 USD PPP. Following the approach previously applied in Sauer et al.<sup>23</sup>, we adjusted all flood damage estimates from NatCatSERVICE and EM-DAT for inflation to the reference year 2011 using country-specific consumer price indices (CPI), i.e., expressing them in the same base year as the GDP data<sup>41</sup>. Therefore, we applied a country specific conversion factor on the CPI-adjusted values reported in NatCatSERVICE (base year 2016) and in EM-DAT (base year 2020), using the ratio of the damage from a 2011 event in the inflation adjusted unit and the damage for the same event in the nominal unit. Consequently, each damage entry in the NatCatSERVICE database recorded for a country *c* in a year *y* was converted according to:

$$\text{damage}_{c,y}(\text{USD}, \text{CPI } 2011) = \text{damage}_{c,y}(\text{USD}, \text{CPI } 2016) \cdot \frac{\text{damage}_{c,2011}(\text{USD}, \text{CPI } 2016)}{\text{damage}_{c,2011}(\text{USD}, \text{nominal})} \quad (1)$$

For the EM-DAT database, this conversion reads:

$$\text{damage}_{c,y}(\text{USD}, \text{CPI } 2011) = \text{damage}_{c,y}(\text{USD}, \text{CPI } 2020) \cdot \frac{\text{damage}_{c,2011}(\text{USD}, \text{CPI } 2020)}{\text{damage}_{c,2011}(\text{USD}, \text{nominal})} \quad (2)$$

To provide recorded damages in the same unit as exposed assets, we additionally converted recorded damages for each country and each year to constant 2011 USD PPP according to:

$$\text{damage}_{c,y}(\text{USD}, \text{CPI } 2011 \text{ PPP}) = \text{damage}_{c,y}(\text{USD}, \text{CPI } 2011) \cdot \frac{\text{GDP}_{c,y}(\text{USD}, \text{real PPP } 2011)}{\text{GDP}_{c,y}(\text{USD}, \text{real } 2011)} \quad (3)$$

### Socio-economic and land use data

The spatially-explicit exposure data used in this study is based on the FLODIS dataset<sup>26</sup> combining satellite imagery of observed floodplains with

impact records and spatially-explicit data on socio-economic indicators, infrastructure, land use and flood protection (FLOPROS). Population data used to calculate exposed population are based on the gridded population of the world version 4 (GPW) dataset<sup>28</sup> and on the Global Human Settlement Layer (GHSL)<sup>29</sup> on a 30" resolution. As only data for the years 2000, 2005, 2010, 2015, and 2020 are provided, we interpolated the years in between to obtain a continuous annual time series of gridded population. Similarly, spatially-explicit time series of Human Development Index and GDP per capita were adopted from Kummu et al.<sup>41</sup> for the years 2000, 2005, 2010, and 2015 and interpolated/extrapolated for the missing years. In order to obtain an annual time series of exposed assets, we followed the approach previously applied in Sauer et al.<sup>23</sup>.

Based on the spatially explicit GDP time series, we generated a time series of gridded asset stock, using annual national data on capital stock and GDP from the Penn World Table (version 9.1)<sup>65</sup>. For each country, the annual ratio of national GDP and capital stock was calculated and smoothed with a 10-year running mean to generate a conversion factor, which was then applied to translate exposed GDP into asset values:

$$\text{exposed asset}_{c,y}(\text{USD}, 2011 \text{ PPP}) = \text{GDP}(\text{USD}, 2011 \text{ PPP}) \cdot \frac{\text{capital stock}(\text{USD}, \text{nominal})}{\text{GDP}_{c,y}(\text{USD}, \text{nominal})} \quad (4)$$

Data on the Critical Infrastructure Spatial Indicator (CISI) and educational institutions for the year 2022 was extracted from the spatially-explicit global dataset of critical infrastructure<sup>44</sup> based on Openstreetmap, providing the number of entities per grid cell on a 360" resolution. Spatially-explicit data on forest cover<sup>45</sup> was resampled from its original resolution of 30 m to 300 m and is based on the year 2010. Data on flood protection standards was included from FLOPROS<sup>46</sup>, providing data on the 1st sub-national layer, i.e., on the province level.

World regions and income groups were defined according to the World Bank Country and Lending Groups from 2021<sup>47</sup>. Low-income economies are defined as those with a GNI per capita, of 1085 USD or less in 2021; lower middle-income economies are those with a GNI per capita between 1086 and 4255 USD; upper middle-income economies are those with a GNI per capita between 4256 and 13,205 USD and high-income economies are those with a GNI per capita of 13,205 USD or more. Development levels were assigned at the local level applying the thresholds provided by the Human Development Reports<sup>48</sup>. Low developed areas are those with an HDI < 0.550; medium developed areas refer to 0.550 < HDI < 0.699; high developed areas are those with 0.699 < HDI < 0.799; very high developed areas have an HDI > 0.799. In this study, we considered annual national income inequality, in terms of the GINI index, which ranges from zero (perfect equality) to 100% (complete inequality)<sup>42,66</sup>.

### Flood exposure

Aiming to generate an indicator reflecting the relevance of floods for a country, we used simulated shares of the national population exposed to floods of a 100-year return period for 188 countries from Rentschler et al.<sup>43</sup>. The underlying flood simulations include fluvial, pluvial, and coastal floods, but deliberately do not account for any protective infrastructure (zero protection level). We think that this indicator is a better proxy for the relevance of floods for a country than shares of affected people derived from reported numbers of affected people and/or observed flood extents because countries which effectively reduced their flood risks in the past have low shares of people affected or even not appear in the records. Thus an observation based indicator would not allow countries with low flood risks from countries like the Netherlands that were prone to floods in the past but were not exposed to floods in the observational study period due to their high protection standards.

### Matching process

To match the satellite observed floodplains from GFD<sup>64</sup> with events reported in the impact databases and with spatially explicit socio-economic and land use data, we followed the matching procedure developed for the FLODIS

dataset<sup>26</sup> for the databases NatCatSERVICE and DFO. Data for displacements recorded in GIDD from IDMC and EM-DAT impacts (asset damage and fatalities) were directly extracted from FLODIS.

To match displacements with GFD events, FLODIS compares event names of IDMC displacement entries with province or district names with matching ISO3 codes of the GADM database<sup>67</sup> on the basis of similarity scores. If the event names match with multiple polygons, the polygons are aggregated to displacement regions. If no matching provinces or districts are found, the national area is used. For fatalities and damages from EM-DAT, FLODIS applies GDIS<sup>68</sup> which contains GIS polygons for each disaster event reported in EM-DAT. The polygons are matched with the GFD flood events. In addition to the spatial conditions, event dates must differ less than 30 days. If more than one GFD entry is matched with an impact event, the entry with a starting date difference of equal or less than 14 days, or, in case no event matches the criteria, with the smallest difference, is kept. If more than one event of an impact database is assigned to a floodplain, the impact metrics of the events are combined. A full description of the methodological approach of FLODIS can be found in Mester et al.<sup>26</sup>.

Analogous to the FLODIS matching procedure, we also matched impact data from NatCatSERVICE with GFD events. The NatCatSERVICE database provides geoinformation on disaster events in singular coordinate format. Events were considered as matches with GFD flood extents only when their coordinates fall within the flooded area. As a temporal condition, event dates of both datasets have to differ less than 30 days.

We further determined exposed assets, the number of affected people as well as the number of affected critical infrastructure units of all 913 events reported in the GFD database. As GFD is based on the DFO, we directly connected exposure to recorded fatalities for all events. We computed exposure by overlaying the linearly inter-/ extrapolated gridded population of the world version 4 (GPW)<sup>28</sup> and gridded GDP Counts<sup>41</sup> as well as the time-invariant Critical Infrastructure<sup>44</sup> datasets with GFD flood extents and calculating the mean of all entities of grid cells touched by the GFD flood extents.

### Event vulnerabilities

In this work, following previous approaches<sup>16–18,30</sup>, we define mortality ( $vul_{Fatalities}$ ) and displacement vulnerability ( $vul_{Displacements}$ ) as the ratio of fatalities (or displacements) of the total exposed population and asset vulnerability as the share of damage to exposed assets ( $vul_{Assets}$ ):

$$vul_{Assets} = \frac{\text{damage}}{\text{exposed asset}} \quad (5)$$

$$vul_{Fatalities} = \frac{\text{fatalities}}{\text{exposed people}} \quad (6)$$

$$vul_{Displacements} = \frac{\text{displacements}}{\text{exposed people}} \quad (7)$$

### Assessing the effect of events without fatalities

For fatalities, a peculiarity arises through the reporting of events without fatalities. In total, NatCatSERVICE counts 218 out of 800 events without fatalities. In doing so, it is not clear whether events with missing information are also reported as events without fatalities (Fatalities = 0). The same applies for the impact data provided by DFO, where 318 out of 913 events are reported without fatalities (Fatalities = 0). In contrast, EM-DAT does not report events without fatalities, so there are no events with Fatalities = 0, only events with missing information (Fatalities = n.a.) are given. Consequently, it is difficult to distinguish between events without fatalities and those with missing information and these events are excluded from the analysis.

On the one hand, these events, if reported correctly, may indicate the successful achievement of the ultimate objective of reducing vulnerability. On the other hand, they represent a singularity within the quantification of

vulnerabilities, as the result is independent of the exposure. Consequently, less effort on vulnerability reduction may be necessary to completely avoid fatalities in areas with lower exposure. This may lead to inconsistencies in the evaluation of relevant determinants influencing vulnerability reduction. In order to account for both, the success in the elimination of fatalities and the dependence on exposure, we studied the effect of events without fatalities in three steps:

- I) We assessed the shares of events without fatalities of the total number of events across years, income or development groups and world regions (Supplementary Figs. S9 and S11–S13).
- II) Similarly, we derived the average number of exposed people per event without fatalities for each year, income- or development group and world region (Supplementary Figs. S9 and S11).
- III) We introduced an alternative vulnerability definition, by adding up a minimal impact to all events to impede that vulnerability becomes 0, according to:

$$vul_{Fatalities+1} = \frac{\text{fatalities} + 1}{\text{exposed people}} \quad (8)$$

This vulnerability definition allows us to assess the frequency of these events, while preserving the exposure component in an additional test (Supplementary Discussion, Supplementary Figs. S8, S10, and S14, Supplementary Table S11). Although EM-DAT does not explicitly report events with Fatalities = 0, we replaced all events with Fatalities = n.a with Fatalities = 0 and used additional tests applying the alternative vulnerability definition (Supplementary Fig. S26).

### Statistical analysis

In order to investigate temporal trends in vulnerabilities, we applied an ordinary least square (OLS) regression on the vulnerabilities converted to the common logarithmic space. The conversion is required, as the individual event vulnerabilities are not normally distributed. To test the robustness of the results, we additionally employed the non-parametric Mann–Kendall–Test<sup>69</sup>. Additionally, we analyzed trends in annual means using both trend testing methods (Supplementary Tables S3–S5, S7–S13). To test the significance of disparities between events and vulnerabilities of different income and development groups as well as between world regions, we applied the non-parametric Kruskal–Wallis–Test<sup>70</sup>.

To test the relationship between vulnerabilities and the socio-economic and structural characteristics listed in Table 1, we used uni- and multivariate regressions models based on ordinary least squares (OLS) and Random Forest Regressors<sup>71</sup>. The parameter settings of the Random Forests, including the number of estimators and random states as well as the maximum depth for each selection of predictors are given in Supplementary Table S10. The number of estimators and the maximum depth were determined by means of a grid search algorithm that iterates through a grid of possible parameter combinations using a cross-validation to yield the optimal model performance<sup>72</sup>. In this assessment the number of random states is fixed to 10 for each Random Forest Regressor. The results are generally insensitive to the number of random states as the standard deviation of the model performance is very low (Supplementary Table S10). We compared model accuracies and improvements through the addition of further drivers, applying a leave-one-out cross-validation (LooCV)<sup>73</sup> to avoid overfitting of the data in an out-of-sample analysis. In a LooCV, the Random Forest is trained on all the data except for one observation and a prediction is made for that observation. The training procedure is repeated n-times, with n representing the number of observations, until each observation was left out once in a training process. This allowed for a model validation despite the limited number of observations. In the multivariate analyses we either use HDI or GDP per capita, respectively either availability of critical infrastructure or availability of educational institutions, as these indicators are strongly related per definition and therefore highly correlated.

### Limitations of satellite-based observations of flooded areas

The flooded areas used in this study are subject to several limitations and uncertainties related to the identification of flooded areas. Although, the flood plains are free of biases encountered in hydrological models, flooded areas derived by means of remote sensing instruments such as the Moderate Resolution Imaging Spectroradiometer (MODIS) are subject to a series of limitations encountered in sensor technologies and image processing<sup>74–76</sup>. In general, these limitations are related to the detection of floods beneath cloud and canopy cover, as well as cloud and mountain shadowing<sup>74–76</sup>. Based on the event records from DFO, the final library of flood maps provided by the GFD covers 913 out of 3127 eligible flood events that co-occurred with MODIS imagery. As every map underwent a quality control process, maps of poor-quality are not included in the analysis. This includes flood events that could not be detected by MODIS or have failed the quality check because of short timescales (flash floods), persistent cloud cover, too small channels of water (below MODIS's 250-m resolution), inaccurate locations, complex terrain such as dense forests and cities<sup>24</sup>. In particular, the under-representation of flash and urban floods limits the scope of this vulnerability study. The quality control process ensures that the flood plains used in this study are a useful representation of the flood event<sup>24</sup>, i.e., the inundation is mapped beyond permanent water bodies, and major parts of the inundation areas are not obscured by cloud cover.

However, there are some limitations encountered in the flooded areas used in this study related to the inundation detection threshold algorithm. For floods in northern latitudes a false positive classification of flooded areas (errors of commission) is more likely than in other areas as low sun angles on dark soil cause a reflectance that imitates water. This may underestimate vulnerabilities in northern latitudes as exposure may be overestimated. Errors of omission are evenly distributed across the globe and do not introduce a systematic bias in the vulnerability assessment. In order to avoid the misclassification of pixels the GFD was developed using 3-day and 2-day composites. Thereby a pixel is only classified as a water pixel if at least half of the observations collected over the corresponding time interval were classified as water. In fast moving water, the temporal resolution of two images per day combined with potential cloud cover may lead to an underestimation of the flood extent. This potential underestimation of the flood extent for some events may cause an underestimation of the exposure, thus an overestimation of vulnerability.

### Data availability

All the data based on EM-DAT, DFO and IDMC generated during this study and required to reproduce the findings are publicly available. Input data from the FLODIS dataset can be accessed at <https://doi.org/10.5281/zenodo.7306882><sup>26</sup>. The data on recorded damage and fatalities are available from Munich Re's NatCatSERVICE, but restrictions apply to the availability of the data, which were provided by Munich Re only for the current study, and so are not publicly available. The input data based on DFO records produced for this study are available at <https://doi.org/10.5281/zenodo.8118213><sup>27</sup>. The data required to reproduce figures is provided as Supplementary Data.

### Code availability

The code required to reproduce the FLODIS input data can be accessed at <https://github.com/BenediktMester/FLODIS>. The code required to reproduce further input data and the analysis can be accessed at [https://github.com/ingajsa/sat\\_obs\\_flood\\_vulnerability](https://github.com/ingajsa/sat_obs_flood_vulnerability).

Received: 7 September 2023; Accepted: 17 April 2024;

Published online: 08 May 2024

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## Acknowledgements

This research has received funding from the German Federal Ministry of Education and Research (BMBF) under the research projects QUIDIC (01LP1907A) and from the European Union's Horizon 2020 research and innovation programme under grant agreement RECEIPT (820712).

## Author contributions

I.J.S., C.O., and K.F. designed the research. B.M. has matched the satellite-observed floodplains with the impact records. B.M., S.Z. and I.J.S. have computed the socio-economic exposure for each event. I.J.S. has analyzed the data. C.O., J.S. and K.F. have supervised the work. I.J.S. and C.O. wrote the manuscript with contributions from all authors.

## Funding

Open Access funding enabled and organized by Projekt DEAL.

## Competing interests

The authors declare no competing interests.

## Additional information

**Supplementary information** The online version contains supplementary material available at <https://doi.org/10.1038/s43247-024-01401-y>.

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**Peer review information** *Communications Earth & Environment* thanks David Muñoz, Colin Doyle and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary Handling Editors: Rahim Barzegar and Martina Grecequet. A peer review file is available.

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