The wider the gap between rich and poor the higher the flood mortality

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Economic inequality is rising within many countries globally, and this can significantly influence the social vulnerability to natural hazards. We analysed income inequality and flood disasters in 67 middle- and high-income countries between 1990 and 2018 and found that unequal countries tend to suffer more flood fatalities. This study integrates geocoded mortality records from 573 major flood disasters with population and economic data to perform generalized linear mixed regression modelling. Our results show that the significant association between income inequality and flood mortality persists after accounting for the per-capita real gross domestic product, population size in flood-affected regions and other potentially confounding variables. The protective effect of increasing gross domestic product disappeared when accounting for income inequality and population size in flood-affected regions. On the basis of our results, we argue that the increasingly uneven distribution of wealth deserves more attention within international disaster-risk research and policy arenas.

"When there is rain or snow, you can make more money", explained a food-delivery worker who had been wading through knee-deep flood-water amid the extreme rainfall of Hurricane Ida in New York City[1]. Despite New York being one of the richest cities in the world, many like him could not afford to miss even one shift. The storm caused a number of fatalities, particularly in illegal basement apartments[2], highlighting the intersection of poverty and inadequate housing conditions. Time and again, disasters expose existing inequalities in a ruthless way[3]. We think that this is alarming since the gap between rich and poor is widening in many countries across the world[4], whilst climate change is also intensifying extreme rainfall patterns and, thus, increasing the magnitude of major flood events[5].

Economic inequality refers to the uneven distribution of income and wealth within and across societies. Within many countries, the widening gap between rich and poor that has developed since the 1980s has overthrown the previously widespread theory of Kuznets[6], which

puts forward that market forces will ultimately reduce inequalities as economies develop[7,8]. Furthermore, research has shown that high levels of income inequality within countries can exacerbate human losses from natural hazards[9–11].

A number of factors can contribute to the relationship between income inequality and mortality from natural hazards, and these relate to both poverty and the disproportionality per se[9–13]. First, a high level of income inequality signals that a large share of the population is living in poverty, which can increase the vulnerability during and after a disaster. For instance, individuals living in poverty may lack the resources needed to prepare or evacuate in the face of a flood[9] (Box 1 presents the case of New Orleans, USA, in 2005). Second, power asymmetries may also generate spatial marginalization, which can exacerbate disaster risk through the concentration of services, resources and flood-protection infrastructure in high-income neighbourhoods[13]. For instance, historical analysis has shown that adaptation efforts are

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BOX 1

The role of inequalities in explaining flood fatalities: the case of Hurricane Katrina in New Orleans in 2005

To illustrate some key mechanisms that explain the relationship between inequalities and flood fatalities, we refer to the flooding of New Orleans in 2005 during the occurrence of Hurricane Katrina[32]. This is a case in point of social and racial segregation resulting in low-income neighbourhoods, which are significantly more vulnerable to flooding[58]. Flood fatalities, in particular, were aggravated in New Orleans for various reasons. First, the levee failures that caused the most severe flooding occurred in low-income neighbourhoods, including the Lower Ninth Ward in the St Bernard bowl area[59]. Second, people in low-income neighbourhoods had limited or no access to cars or other forms of transportation, and consequently many of them were unable to evacuate in time[60]. Third, most people in these areas lived in mobile or stick-built houses, which were highly susceptible to flooding[61]. Last, severe contamination of the air occurred after the flooding in these areas, as most of the industrial and toxic sites of New Orleans were located in low-income neighbourhoods[62].

more likely to take place when the interests of those with power and resources are impacted directly[14].

Despite this, there has been limited empirical research on the relationship between economic inequality and the human losses from floods, primarily due to a lack of data[14–16]. Previous studies have limitations in scope, using either single-case studies (see, for instance, ref. 17) or coarse and ageing datasets (see, for instance, ref. 9). However, with increasing data availability on floods, their impacts, human settlements and socioeconomic indicators, there is now an opportunity to investigate this topic in more detail.

In this study, we investigate the extent to which unequal countries also suffer higher flood mortalities. We conduct a global analysis of the relationship between income inequality and flood mortality in 67 middle- and high-income countries (MHICs) over the past 29 years. We limit the study to MHICs for the sake of comparability, as the baseline capacity to mitigate disasters varies considerably between developing and advanced economies. More specifically, our working hypothesis of how income inequality may affect disaster vulnerability, through power asymmetries and spatial marginalization, relates closely to the concept of relative poverty. This is not generalizable to low-income countries (LICs), however, in which the level of absolute poverty and the lack of countrywide resources tend to be the dominant drivers of human vulnerability[18]. While acknowledging the importance of studying disaster risk in LICs, who are burdened with the highest mortality rates globally[5], our study aims to highlight the role of economic inequality in advanced economies since they have, in theory, the financial resources needed to prevent flood fatalities. To highlight further the role of income inequality in the wealthiest countries, and to corroborate the results with a different sample, we also conduct a complementary analysis on 28 member nations of the Organization for Economic Cooperation and Development (OECD).

The level of inequality within an economy depends on the distribution of both income (a flow) and capital (a stock). We represent economic inequality with the distribution of income, however, since data on the distribution of capital are still limited for many countries. For this purpose we use the Gini index of disposable income, which ranges from zero (perfect equality) to 100% (complete inequality). The Gini index is the most commonly used indicator for measuring income inequality, despite its limitations such as being most sensitive to changes in the middle part of the distribution and different income distributions resulting in similar index values[19]. Alternative metrics for measuring income inequality, such as the Atkinson index and the Palmer ratio, are also available but we choose to use Gini for the purpose of international coverage and comparability[20].

Here, we link income inequality to flood mortality in MHICs by combining mortality records from 573 major flood disasters that occurred between 1990 and 2018 with settlement maps and socioeconomic indicators (Fig. 1). Initially, we explore these data to highlight patterns of flood mortality across space, time and economic conditions. We then test if there is an association between flood mortality and income inequality after accounting for potentially confounding variables, such as average living standards and the level of flood exposure. Throughout the article we represent flood exposure with the number of individuals living in the flood-affected administrative regions in the year of the event. Specifically, we ask the following questions. (1) How have income inequality, average living standards and flood mortality changed over the study period? (2) How do flood mortality levels vary across continents, levels of inequality, levels of average living standards and degree of urbanity? (3) Is income inequality associated with flood mortality after accounting for potentially confounding variables such as average living standards and flood exposure? We emphasize that we cannot infer causality with our data, but our findings aim to shed light on the relative importance of various independent variables and thus enhance our understanding of how the distribution of wealth may influence disaster outcomes in advanced economies.

Results

We found that a majority (49 out of 67) of the flood-affected MHICs in our sample experienced a rise in income inequality between 1990 and 2018, with 21 of these countries being OECD nations (Fig. 2). All countries except for Venezuela saw an increase in average living standards over the same period, in terms of the per-capita real gross domestic product (GDP). The sample as a whole experienced slightly larger changes in the Gini index in absolute terms (3.7 percentage points (pp)) compared with the OECD-nation subgroup (3.3 pp) (Supplementary Table 3).

All 573 records from the MHICs have a median mortality rate of 2.9 fatalities per million potentially exposed people, while the 372 fatal records have a median mortality rate of 13.4. The 265 records from the OECD subgroup have a median mortality rate of 0.8 fatalities per million potentially exposed, of which the 158 fatal records have a median mortality rate of 6.7. Across the continents, we found flood mortality to be the highest in Africa, Asia and the Americas, both in terms of the mortality rates and the absolute fatality numbers (Extended Data Fig. 1). The records from Europe and Oceania report significantly lower flood mortality levels. We also found that only Asia experienced significantly decreasing trends in mortality levels over the study period in terms of the mortality rates (Fig. 3) and absolute fatality numbers (Supplementary Fig. 2). The other continents do not show significant trends in flood mortality, nor does the sample as a whole (Supplementary Table 4). Specifically, we did not find a reduction in flood mortality in member states of the European Union (EU) when comparing the periods before and after publication of Directive 2007/60/EC of the European Parliament on flood risks in 2007[21] (referred to as the Directive throughout this article). The period following the Directive holds fewer records of major flood events in the EU member states, but these also report significantly higher mortality levels in terms of the mortality rates (Fig. 3) and absolute fatalities (Supplementary Fig. 2).
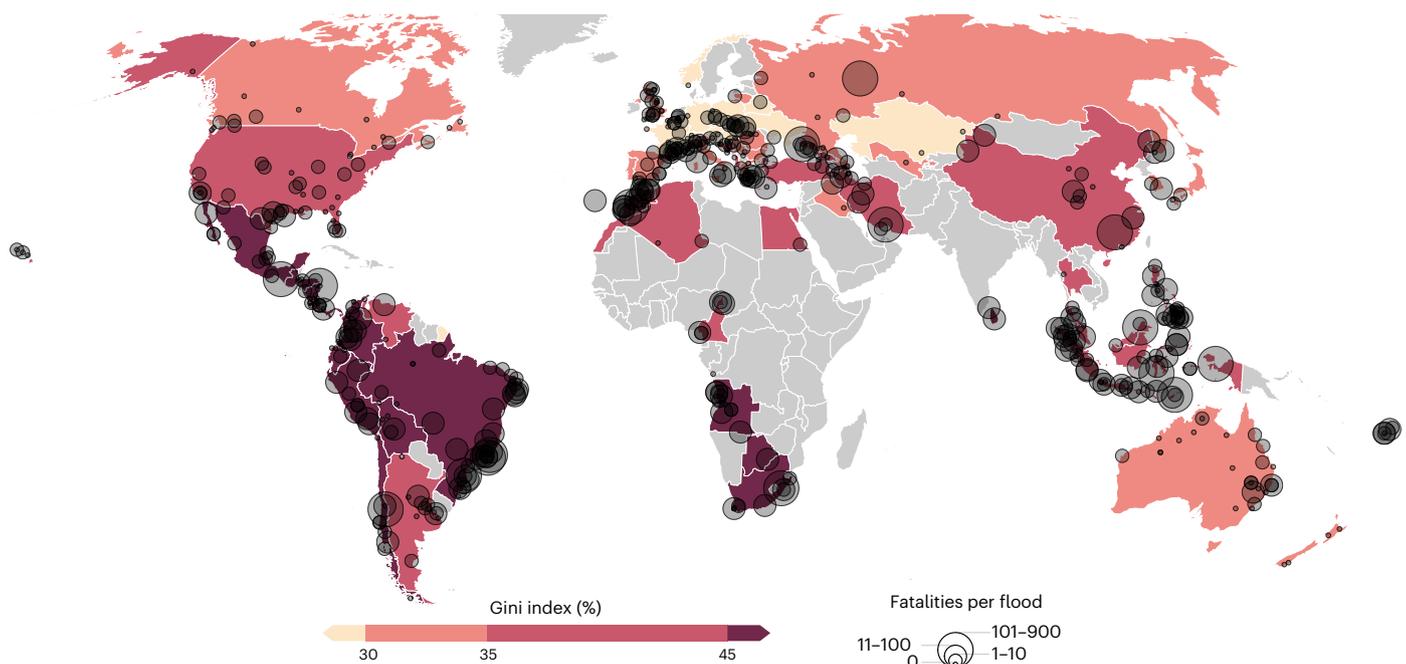
Fig. 1 | Income inequality and flood fatalities in 67 MHICs. This map displays 573 major flood disasters (dots) that occurred between 1990 and 2018, with the size of the dots indicating the number of reported flood fatalities, and the colour of the countries indicating their average level of income inequality across the sample. The flood disasters are reports from the Emergency Events Database (EM-DAT[31]) that have been georeferenced to districts (or smaller subdivisions) using the Geocoded Disasters dataset (GDIS)[44]. Basemap from Natural Earth (https://www.naturalearthdata.com/).

Our initial data screening also revealed a significant correlation between disposable income distribution and flood mortality rates, with countries in the low-Gini group recording a 26-fold lower mortality rate compared with countries in the high-Gini group (Fig. 4). In addition, countries with higher average living standards, as measured by the per-capita real GDP, exhibited significantly lower flood mortality rates, with a 22-fold lower mortality rate in the high-GDP group compared with the low-GDP group (Fig. 4). We also identified that flood disasters affecting at least one major urban centre had significantly higher fatality numbers compared with more rural disasters, although the urban mortality rates were lower due to larger exposure estimates (Extended Data Fig. 2). We found similar results when grouping the disasters according to the share of potentially exposed individuals living in high-density clusters (Extended Data Fig. 2).

In a negative binomial mixed-effect model of flood fatalities in MHICs, for a 3 pp increase in the Gini index we found a 16% increase in fatalities (that is, the risk ratio (RR)), with a 95% confidence interval (CI) of 1–33% (Fig. 5 and Supplementary Table 5). This effect was even stronger for the OECD nations, for which we found a 25% increase in fatalities (RR) with a 3 pp increase in the Gini index (95% CI, 1–54%) (Supplementary Table 6). Unlike the Gini index, the per-capita real GDP was not significantly related to flood fatalities when controlling for other variables (Supplementary Tables 5 and 6). We also found that the level of exposure was the most important variable when modelling flood fatalities in MHICs (Supplementary Table 7), although we did not detect a significant effect of exposure on fatalities in OECD nations (Supplementary Table 8). Other variables, such as the share of exposed individuals living in high-density clusters, were not found to be significantly related to flood fatalities (Supplementary Tables 5 and 6).

Discussion

We show that the MHICs who suffered the highest human flood losses between 1990 and 2018 are also burdened by high levels of income inequality. Our regression results show that the association between income inequality and flood mortality persists after accounting for the per-capita real GDP, the level of flood exposure and other confounding variables. Simultaneously, although most MHICs in the sample have seen an improvement in average living standards since 1990, a majority has also become more unequal in terms of income distribution.

Our initial data screening showed that flood mortality tends to be higher in countries that have lower average living standards in terms of the per-capita real GDP. However, this effect did not persist in the regression analysis when accounting for income inequality and the level of flood exposure. We think that these results underline the importance of the current discussion about the shortcomings of the GDP to measure human wealth and progress, as highlighted recently by the United Nations secretary-general António Guterres[22]. Disaster-risk research and policy arenas arguably need to give more attention to this, and ensure that both exposure levels and inequality are accounted for in quantitative vulnerability assessments.

Room for improvement in vulnerability assessments

Economic inequality is often missing in quantitative vulnerability assessments by the disaster-research community. One example of how the research community is missing the role of inequality is the tendency to use national economic development levels, such as the per-capita GDP, as a proxy for vulnerability in cross-national disaster-risk studies[15,23–26]. These types of study often correlate human loss rates with such indicators of economic development, and conclude how vulnerability is decreasing with increased country wealth. Indeed, there is often a negative relationship between mortality rates and economic development (Fig. 4), although this relationship is also highly disputed within the literature[15]. Our regression results (Fig. 5 and Supplementary Table 7), in agreement with previous empirical studies[9,11], show that income inequality has a significantly larger effect on disaster mortality in MHICs, and we question why this relationship is repeatedly left out from the analysis and conversation. We attribute this to the dominance of GDP and growth narratives in international disaster-risk research and
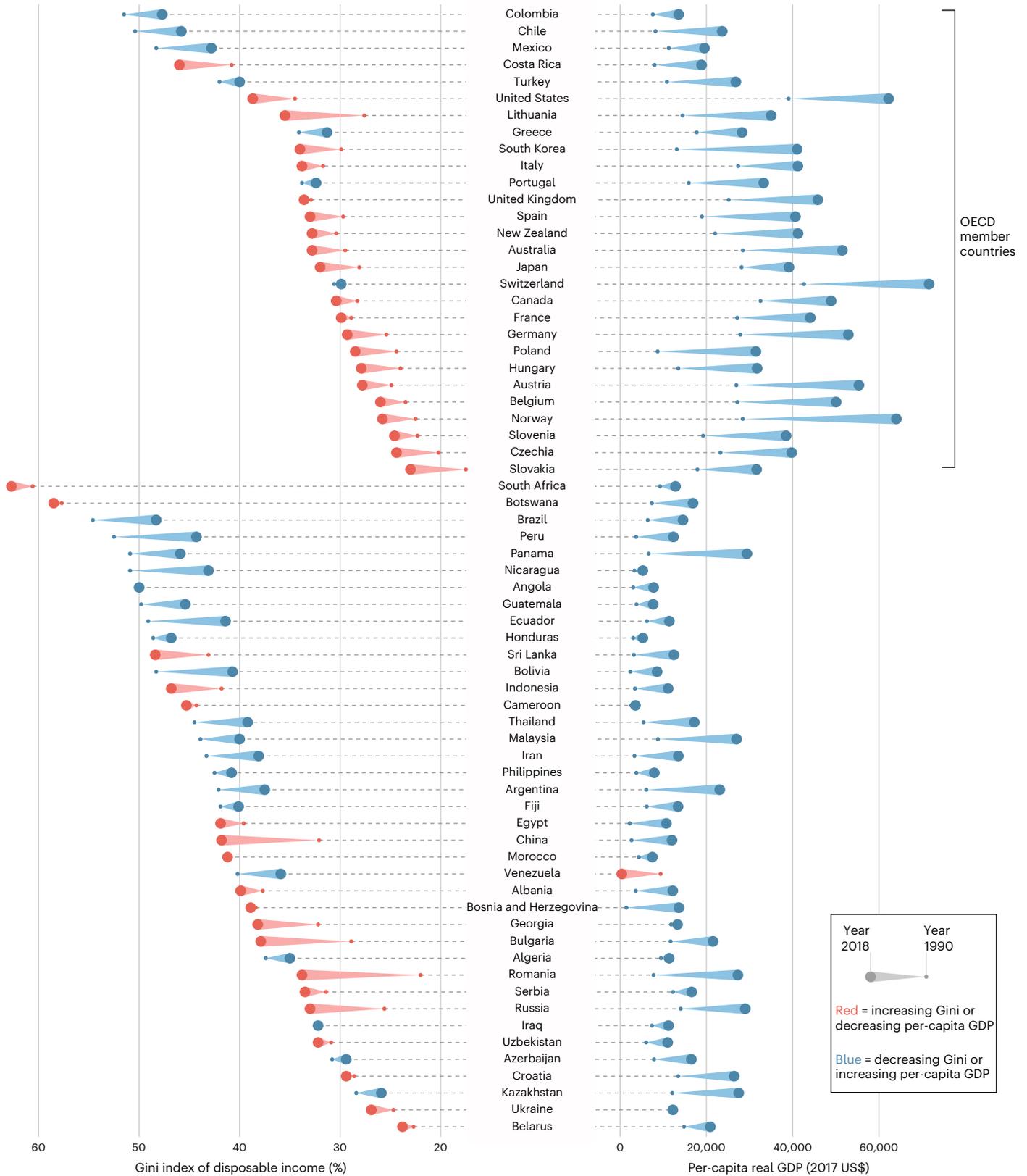
Fig. 2 | Changes in income inequality and average living standards among 67 MHICs. This dumbbell plot shows the income inequality and average living standards in 2018 (large dots) compared with 1990 (small dots) for countries that also experienced at least one major flood disaster during the same period. All countries apart from Venezuela experienced a rise in average living standards, but a majority also experienced a rise in income inequality since 1990. The colours indicate the direction of change. In the case of a missing yearly value, we used the closest available yearly value. In the source data table we have highlighted the instances in which the available yearly value was more than three years apart from 1990 (n = 7) or 2018 (n = 9).
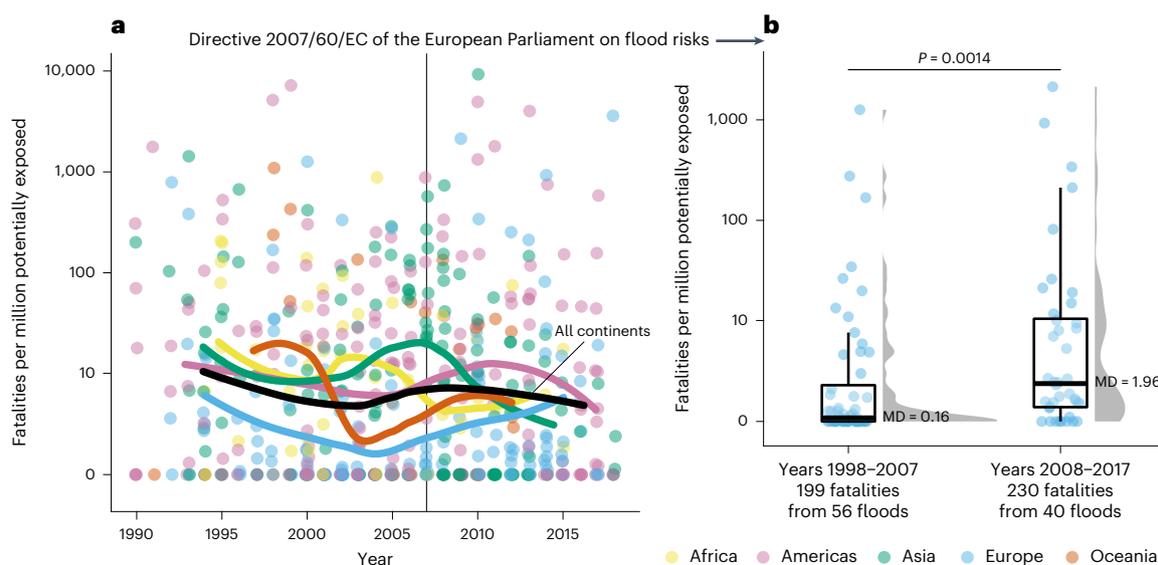
Fig. 3 | Major flood disasters in MHICs have generally not become less fatal since since 1990. a, Scatter plot of mortality rates for 573 flood disasters (dots) over time, with the black trend line referring to all continents. Only Asia has a significant trend of decreasing mortality rate according to a two-sided Mann–Kendall test ($P = 0.003$). Supplementary Table 4 provides P values across all continents. The trend lines are fitted using local polynomial regression. **b**, Box plot showing disasters (dots) in EU states, ten years before and after the Directive of 2007. The period following the Directive had fewer flood disasters compared with the period before, although more flood fatalities were also reported. The dots indicate individual observations; the box hinges indicate the 25th and 75th percentiles, the centre line indicates the median value (MD) and the whiskers indicate the interquartile range multiplied by a factor of 1.5. The P value refers to a two-sided Wilcoxon test comparing group means.

policy arenas. Today it is well known that economic growth does not benefit everyone[4]. Using an average value thus conceals the uneven vulnerability across and within societies, and might not be the optimal way to represent vulnerable parts of the population, as our findings expose.

By contrast, quantitative disaster-risk studies on national, regional or urban levels frequently use social vulnerability indices as a proxy for human vulnerability. These indices often combine demographic data with socioeconomic data (such as the absolute income level, employment level and education level)[27,28] and can be used for mapping vulnerability hotspots and their overlap with hazard zones or disaster losses. This can be a very valuable approach, which unfortunately is difficult to conduct on larger scales due to data limitations. Our results highlight the importance of considering underlying drivers, such as economic inequality, when interpreting these regional maps of vulnerability gradients (see, for instance, ref. 29). This becomes particularly important when forming policy recommendations. For example, floodplain regulations aimed at decreasing flood exposure may not benefit individuals living in illegal housing conditions due to a lack of affordable housing.

Data gaps in cross-national disaster research
As anticipated, our estimated median mortality rate across the MHICs is lower than a previously reported global mortality rate of 40 fatalities per million exposed people, as exposed in ref. 26. Our sample does not consider LICs, who generally suffer higher mortality rates than MHICs[5]. Methodological differences in deriving the exposure estimates will also affect the resulting rates. It is likely that our exposure estimations are systematically overestimated as we consider the number of potentially exposed individuals, that is, the total number of people living in the affected regions during the year of the event. This rather rough exposure proxy is not ideal, and even if we would have been able to distinguish between flooded and dry areas within the affected regions, we would still not have been able to account for the number of evacuated individuals. Taken together, limitations like these pinpoint the persisting difficulty of collecting data on human flood exposure for cross-national research.

Our MHIC data from major flood events between 1990 and 2018 conveyed limited temporal variations in flood mortality levels; we could not detect any significant trends, except for Asia. We should, however, sound a note of caution with regard to these findings, given limitations in the study period length and sample size. Over the past century, the world has seen a significant decline in flood mortality rates, particularly in LICs (see, for instance, refs. 26,30). In addition, our sample includes only major disasters recorded in the international EM-DAT database[31] and does not consider smaller flood disasters or instances where a flood hazard did not result in a disaster.

The role of institutional adaptation
Previous research has suggested that the relationship between income inequality and flood management may be related to institutional adaptation[14]. This is one potentially important factor that our observational dataset misses being able to capture. Thus, it is crucial to conduct more research in this field to further understand the underlying mechanisms and potential confounding factors. Our study was able to provide some insight on one important milestone of institutional adaptation, the European Directive of 2007[21]. Our analysis of data from EU member states revealed that while the number of flood disasters decreased after the Directive's implementation, the floods that did occur were more fatal compared with the period before the Directive.

However, it is important to note that these findings are based on a limited number of years and should be treated with caution. In addition, it is possible that the Directive has positively contributed to preventing multiple disasters, which would not be captured by this analysis. Despite this, our findings suggest that major flood disasters were more fatal in the period following the Directive compared with the period before it—both in terms of absolute fatality numbers and mortality rates. Further examination is needed to determine whether this is a coincidence or due to other factors such as climate change, socioeconomic development in flood-prone areas (despite the Directive) or even to the unintended consequences of flood management in the form of a safe development paradox[32].
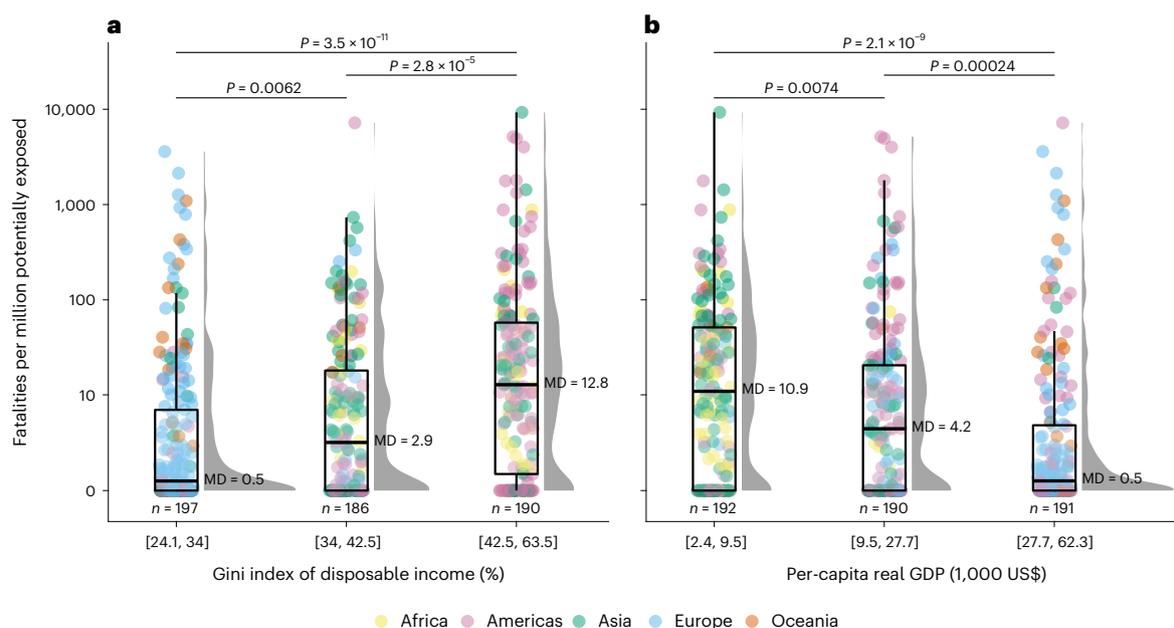
Fig. 4 | Flood mortality rates across gradients of income inequality and average living standards. a,b, Box plots showing the mortality rates of 573 flood disasters (dots), with each group containing a third of the sample and the dot colour indicating the continent. The mortality rates tend to be lower in more equal countries (**a**) and in countries with higher average living standards (**b**). The dots indicate individual observations; the box hinges indicate the 25th and 75th percentile, the centre lines indicate the MD and the whiskers indicate the interquartile range multiplied by a factor of 1.5. The *P* values refer to pairwise two-sided Wilcoxon tests comparing group means.

We also emphasize that the relationship between economic conditions and disaster impacts is complex and bidirectional. Economic conditions before a disaster, which are referred to as ex ante conditions, may influence the outcome of the disaster, while the disaster itself can also have an impact on post-disaster economic conditions, referred to as ex post conditions. Previous ex post studies have focused primarily on the effects of disasters on GDP[15]. However, case studies also suggest that disasters can increase economic inequality, such as in Germany[33] and Brazil[34]. Our study focuses on the association between ex ante national levels of income inequality and disaster outcomes. It is possible that the disasters in turn can exacerbate existing inequalities and affect economic conditions. Through the use of yearly estimates of the economic indicators, our analysis considers the potential influence of previous disasters. However, we hypothesize that the impact of local flood events on the national income distribution would be limited.

Closing the income gap as disaster-risk reduction

As inequalities tend to increase flood vulnerability, closing the income gap holds great potential as a strategy for disaster-risk reduction. It enables risks across multiple hazards to be reduced simultaneously, that is, more unequal societies are not only more vulnerable to floods, but also to pandemics[35], droughts[36] and other disasters. It should be noted that these types of positive synergies are more difficult to achieve with traditional strategies of disaster-risk reduction. Flood-protection structures, for example, such as levees or flood-control reservoirs, can (1) deteriorate ecological values[37], (2) have negative side effects with respect to other hazards[38] or (3) generate unintended consequences, including the safe development paradox[32]. The positive synergies from reducing economic inequality also spill over into other Sustainable Development Goals (SDGs)[39]. Recent research has, for instance, showed that diminishing income inequality has a larger impact on reducing global poverty compared with economic growth[40].

In conclusion, we show that MHICs burdened by income inequality have suffered the largest human losses from major flood disasters during the past 29 years. Simultaneously, a majority of these countries have become more unequal. These findings raise several important questions that require further investigation. Specifically, the mechanisms by which income inequality affects flood mortality are not yet fully disentangled. How our findings transcend across geographical locations and hazard types also need further examination. Thus, we urge disaster researchers to continue to explore the connections between the SDGs for eradicating poverty (SDG 1), reducing inequalities (SDG 10) and reducing disaster mortality through climate action (SDG 13). Closing the income gap can save lives in the face of climate change, and this is achievable through public policy choices.

Methods

We tested the association between income inequality and flood mortality at the country level by collecting and statistically analysing data on disaster impacts, human flood exposure and socioeconomic conditions from a number of international databases. The explorative and statistical analyses were performed using R v.4.1.3 (ref. 41), while the population and settlement data were analysed using Google Earth Engine[42]. All our statistical analyses uses a significance level of 5%.

Study extent

Owing to data reliability and comparability reasons, only floods occurring in MHICs between 1990 and 2018 were included in the study: 573 events in 67 countries. We also analysed records from the OECD nations separately, 265 events in 28 countries, to highlight the role of income inequality in the wealthiest countries. As stated in the introduction, we limited the study to MHICs primarily due to comparability reasons and because we aim to shed light on the role of inequality in advanced economies. We use the income class according to the World Bank Atlas method[43], based on the per-capita GNI (gross national income).

Flood disaster records

The number of fatalities per flood disaster is the outcome variable in our analysis, as reported in the international disaster database EM-DAT[31]. EM-DAT records disasters that fulfil at least one of the following criteria:
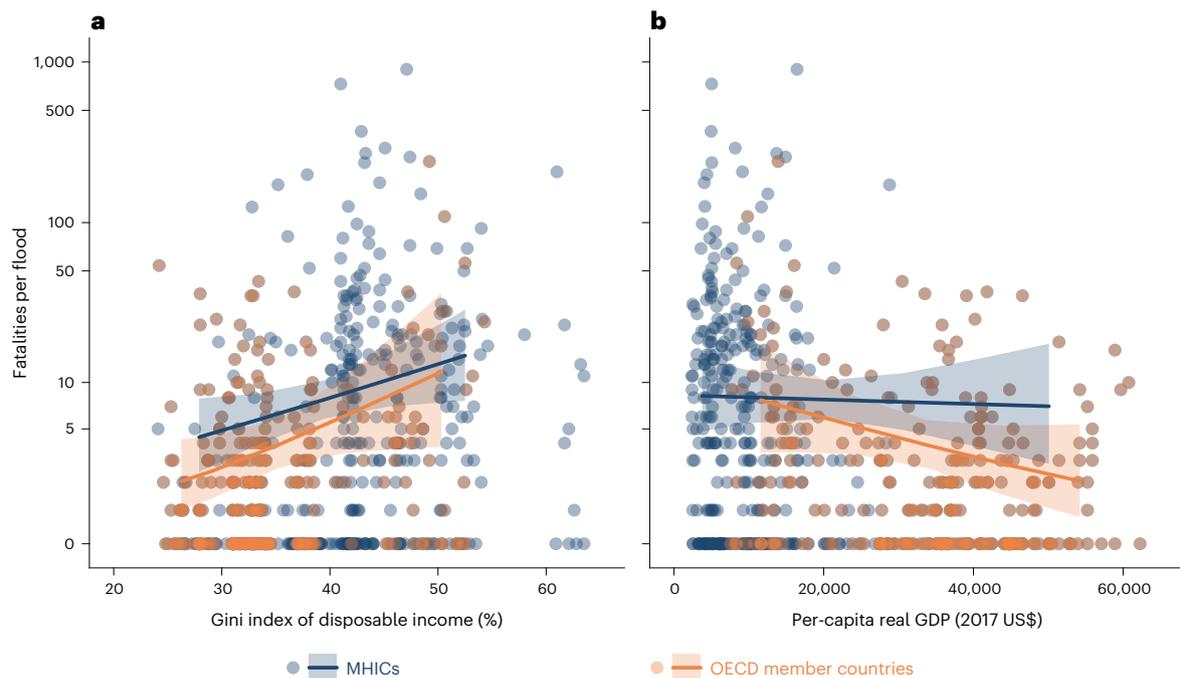
Fig. 5 | Model estimations of flood mortality, income inequality and average living standards. a,b, Scatter plots of 573 flood disasters (dots) that occurred between 1990 and 2018 in 67 MHICs (blue), of which 265 occurred in 28 OECD countries (orange). **a**, Unequal countries tend to experience a higher flood mortality. **b**, Higher average living standards show a limited effect on flood mortality in MHICs and OECD nations; this variable was not significantly related to flood fatalities when controlling for other variables. The lines represent the mean estimations of the negative binomial model (all covariate variables included, unstandardized) with 95% CIs denoted by the shaded areas.

≥10 fatalities, ≥100 affected people, emergency state declaration and/or an international assistance call. We included EM-DAT records classified as riverine floods, coastal floods, flash floods and tropical cyclones (database accessed 7 December 2022).

To control for human flood exposure, we only included records from EM-DAT that were also geocoded by the GDIS database[44]. The developers of GDIS geocoded EM-DAT records by matching the location description with one or more administrative subdivisions in the GADM database of Global Administrative Areas (v.3.6; https://gadm.org/). GADM includes administrative subdivisions at various levels, including state and province boundaries (level 1), county and district boundaries (level 2) and smaller administrative boundaries (level 3). Each disaster record has been geocoded to administrative regions at level 1, 2 and/or 3, depending on the location description text in EM-DAT[44]. The subdivision level to which a record is geocoded depends on the specificity of the location description in EM-DAT and does not necessarily reflect the extent of the actual disaster[44]. Therefore, we included only records geocoded to level 2 and/or 3. Level 1 subdivisions are typically five times larger than level 2 subdivisions and around ten times larger than level 3 subdivisions. Including records geocoded to level 1 would have resulted in considerably larger exposure estimates, potentially biasing the analysis.

Population and settlement data

To estimate the number of potentially exposed people and the degree of urbanity per flood, we utilized three Global Human Settlement (GHS) products: population grids (GHS-POP) at 250 m spatial resolution[45], settlement grids (GHS-SMOD) at 1,000 m spatial resolution[46] and the urban centre database (GHS-UCD)[47]. GHS-SMOD provide settlement maps categorized by degree of urbanization: rural, low-density clusters and high-density clusters. GHS-UCD offers the location and attributes of urban centres around the world.

We calculated the total number of potentially exposed individuals

for each record using the population data from GHS-POP. The degree of urbanity was determined by calculating the percentage of the potentially exposed population living in high-density clusters using GHS-SMOD. Both GHS-POP and GHS-SMOD are available as global seamless raster files for the years 1990, 2000 and 2015. We derived yearly estimates through linear interpolation. For the years 2016, 2017 and 2018, we assigned the same values as in 2015. We also calculated the total settlement area for each record using GHS-SMOD. One record was excluded from the analysis as it did not contain any inhabitants according to GHS-POP, which we deemed unrealistic. We also used GHS-UCD to identify the records whose affected regions contain at least one urban centre. We considered the degree of urbanization as a potential confounding variable, since a previous cross-country literature report has identified disparities between urban and rural areas as a significant contributor to overall inequality within countries[48].

Economic and demographic data

We obtained country–year observations of income inequality from the Standardized World Income Inequality Database v.9.1 (SWIID)[20,49] as the Gini index of disposable (post-tax, post-transfer) household income. We chose the SWIID as the data source since it provides data on disposable income, and the data-collection protocol aims to maximize both coverage and comparability[20]. Nonetheless, some country–year records were missing. When possible, we assigned missing values with the closest available value, at most three years before or after. As mentioned in the introduction, there are alternative metrics to represent economic inequality. However, the global databases that offer these alternative metrics do not provide data on disposable income, nor do they typically have the same coverage as the SWIID. Nonetheless, the choice of inequality metric is particularly influential for ex post studies that investigate mechanisms behind changes in economic inequality. However, for ex ante analyses that investigate the relationship between pre-disaster levels of economic inequality and disaster impacts, such

as in this study, the choice of metric does not influence the results considerably, since the inherent ranking of countries is similar across inequality metrics.

To compare relative living standards across countries and over time, we used the expenditure-side real GDP at constant 2017 prices in US dollars from the Penn World Table v.10.0 (refs. 50,51). This measure is adjusted to price changes, such as inflation[50]. We converted the GDP variable to per-capita terms using national population totals from the same database.

To control for the potential effect of the population age structure on income distribution, we used country–year observations of the proportion of individuals in the country aged 65 or older from the World Development Indicators database of the World Bank[52]. This demographic variable was deemed crucial as an ageing population has previously been shown to impact economic inequality[53,54].

Initial data exploration
We calculated mortality rates for all records by dividing the reported fatality numbers with the number of individuals living in the flood-affected region in the year of the event. We examined if and how the rates varied across space, time and levels of income inequality and economic development. We used non-parametric Wilcoxon tests to compare the group means. We then analysed whether or not the flood mortality levels had changed over the study period, in terms of the absolute fatality numbers and mortality rates. For this purpose, we used non-parametric Mann–Kendall tests to detect trends. Specifically, we compared mortality levels in EU member states ten years before and after the European Directive of 2007.

We also explored if and how flood mortality varied across degrees of urbanity, represented using two metrics. First, we grouped the records according to the binary variable that identified the records whose affected region contained at least one major urban centre according to GHS-UCD data. In addition, we grouped the records based on the share of potentially exposed people living in high-density clusters.

Regression analyses
In this study, we used an unbalanced panel structure model to analyse the relationship between flood fatalities and socioeconomic factors, with the unit of analysis being an individual flood event i occurring in country j during year t. The model specification is outlined in equation (1):

$$\text{FATALITIES}_i = (\beta_0 + b_{0j}) + \beta_1 \text{GINI}_{jt}$$
$$+ \beta_2 \text{GDP}_{jt} + \beta_3 \ln(\text{POT\_EXP}_{it})$$
$$+ \beta_4 \ln(\text{SETTL\_AREA}_{it}) + \beta_5 \text{HDC}_{it} \quad (1)$$
$$+ \beta_6 \text{POP\_65}_{jt} + \beta_7 \text{YEAR}_i + \varepsilon$$

A mixed-effects approach was used, with a random intercept term (b_{0j}) per country to account for variations in the baseline risk across countries. The random effect thus takes into account the lack of independence of records coming from the same country, for instance due to differences that we are not representing with our data, including flood propensity. The response variable, FATALITIES_i, represents the number of reported fatalities from each flood event. The covariate variables included the Gini index of disposable income (GINI_{jt}), the per-capita real GDP (GDP_{jt}), the number of individuals potentially exposed to the flood event (POT_EXP_{it}), the area of settlements in the affected regions (SETTL_AREA_{it}), the proportion of potentially exposed individuals living in high-density clusters (HDC_{it}), the proportion of individuals aged

65 or older in the country (POP_65_{jt}) and a time dummy variable (YEAR_i) to control for temporal changes. β_0 is the average model intercept, β_{1-7} are the regression coefficients for each covariate variable and ε is the error term.

To assess the significance of various variables in relation to flood fatalities, we used a negative binomial generalized linear regression model. This method was chosen due to its appropriateness for count data with an overdispersion of error, and the models were fitted using maximum likelihood estimation with the R package glmmTMB[55]. To support our analysis, we provide summary statistics of the variables at the sample and group level in Supplementary Tables 1 and 2, respectively.

We designed two versions of the regression models, varying the degree of transformation of the covariate variables as seen in Supplementary Fig. 1. In the first main version, we aimed to estimate the effect of changes in the Gini index and per-capita real GDP on the flood mortality. Using data from 1990 to 2018, we scaled these variables to the units of 3 pp and US$10,000, reflecting the changes experienced by the study sample (Supplementary Table 3). All variables were centred and two highly skewed variables (potentially exposed individuals and the total settlement area) were log-transformed. In the second (standardized) version, we aimed to evaluate the relative importance among the independent variables. To this end, we standardized all covariate variables. Before this, we log-transformed the two highly skewed variables.

Model diagnostics
To evaluate the linearity assumption of the negative binomial regression, we conducted spline regression on the Gini index and per-capita real GDP variables (Supplementary Fig. 3). Each variable was replaced with a natural cubic spline with three knots. The linearity assumption holds well for the main model that includes observations from all 65 MHICs. Limiting the sample to records from the OECD nations, however, gives more variable and uncertain model estimates due to the smaller sample size.

In addition to the linearity assessment, we performed residual diagnostics for the models using the R package DHARMa[56] with 1,000 iterations. The negative binomial model structure generally fits the data well. The Kolmogorov–Smirnov test of the main statistical model using observations from MHICs indicates a significant deviation from the expected negative binomial distribution. However, the corresponding quantile–quantile plot (or qq plot) does not show a large deviation from the straight line (Supplementary Fig. 4). Using observations from the OECD nations resulted in slightly less problematic residuals (Supplementary Fig. 5). Standardizing all covariate variables also improved the model fit (Supplementary Fig. 6). Dropping the random effect, however, resulted in more problematic residuals (Supplementary Fig. 7) and a lower model quality in terms of the Akaike information criterion (Supplementary Tables 5–8). On the basis of this, we chose to include the random intercept term in the full model specification, even though 65 out of 67 country estimates were not significantly different from the model estimation (Supplementary Fig. 8).

Methodological limitations
It is important to note the limitations of the present study, which is an observational study performed at the country level, using measures of association to quantify the relationship between flood mortality and income inequality. Although the results suggest a correlation between income inequality and fatality numbers, other methods are needed to indicate causality. In addition, the Gini index is an aggregate metric, which may obscure underlying variables, and here we control for only a few.

Furthermore, the relationship between disaster outcomes and socioeconomic factors is highly context-specific and complex, both across and within countries. The top-down approach of cross-national research simplifies this complexity. We acknowledge that the scale

matters, and a local study would have more potential for disentangling complex processes. Cross-national studies also have their own benefits, and we think it is important that research is conducted on a variety of scales. In addition, the limited number of data points per country prevented the inclusion of a random slope term, which would have provided further information about how the relationship between the variables varies across groups. The level of significance should also be interpreted with a certain amount of caution in the OECD models due to the smaller sample.

Data from global databases have limitations. For instance, we proxy flood exposure for the number of individuals living in the flood-affected administrative regions in the year of the event. This is a rough proxy which does not distinguish between flooded and non-flooded areas within these regions. Moreover, the intensity of the flood events is not taken into account. The disaster database EM-DAT records only major disasters, meaning that smaller disasters and instances where a flood hazard did not result in a disaster (that is, 'success stories') will be missed. The number of fatalities is a relatively straightforward disaster outcome to measure compared with, for example, economic damages and the number of affected individuals, although the accuracy will nonetheless vary across records[57].

Finally, it is important to note that our sampling scheme affects the distribution of sample sizes across continents. A majority of the records in the final sample occurred in the Americas (33%), followed by Europe (29%), Asia (23%), Africa (9%) and Oceania (6%). However, this distribution does not necessarily reflect the true flood frequency for each continent. One reason for this is that the study considered floods only from MHICs. In addition, records that were geocoded to administrative regions at level 1 were excluded from the final sample. This affected some countries more than others. For example, a majority of the records from China in the GDIS database were geocoded to administrative regions at level 1 and were thus excluded from the final sample.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
All data used in this analysis come from publicly available sources. The compiled datasheets that support the findings of this study are available via Zenodo at https://doi.org/10.5281/zenodo.7547323. Source data are provided with this paper.

Code availability
Custom codes to replicate all tables, figures and results of this study are available via Zenodo at https://doi.org/10.5281/zenodo.7547323.

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Extended Data Fig. 1 | Flood mortality across continents. This figure presents box plots showing 573 flood disasters (dots) occurring between 1990 and 2018 in middle- and high-income countries. Africa, the Americas and Asia have significantly higher flood mortality compared to Europe and Oceania, both in terms of absolute fatality numbers (**a**) and mortality rates (**b**). The dots indicate individual observations, the box hinges indicate the 25th and 75th percentiles, the centre lines indicate the median value (MD), and the whiskers indicate the interquartile range multiplied by a factor of 1.5. The P values refer to pairwise two-sided Wilcoxon tests comparing group means, using Europe as the reference group.
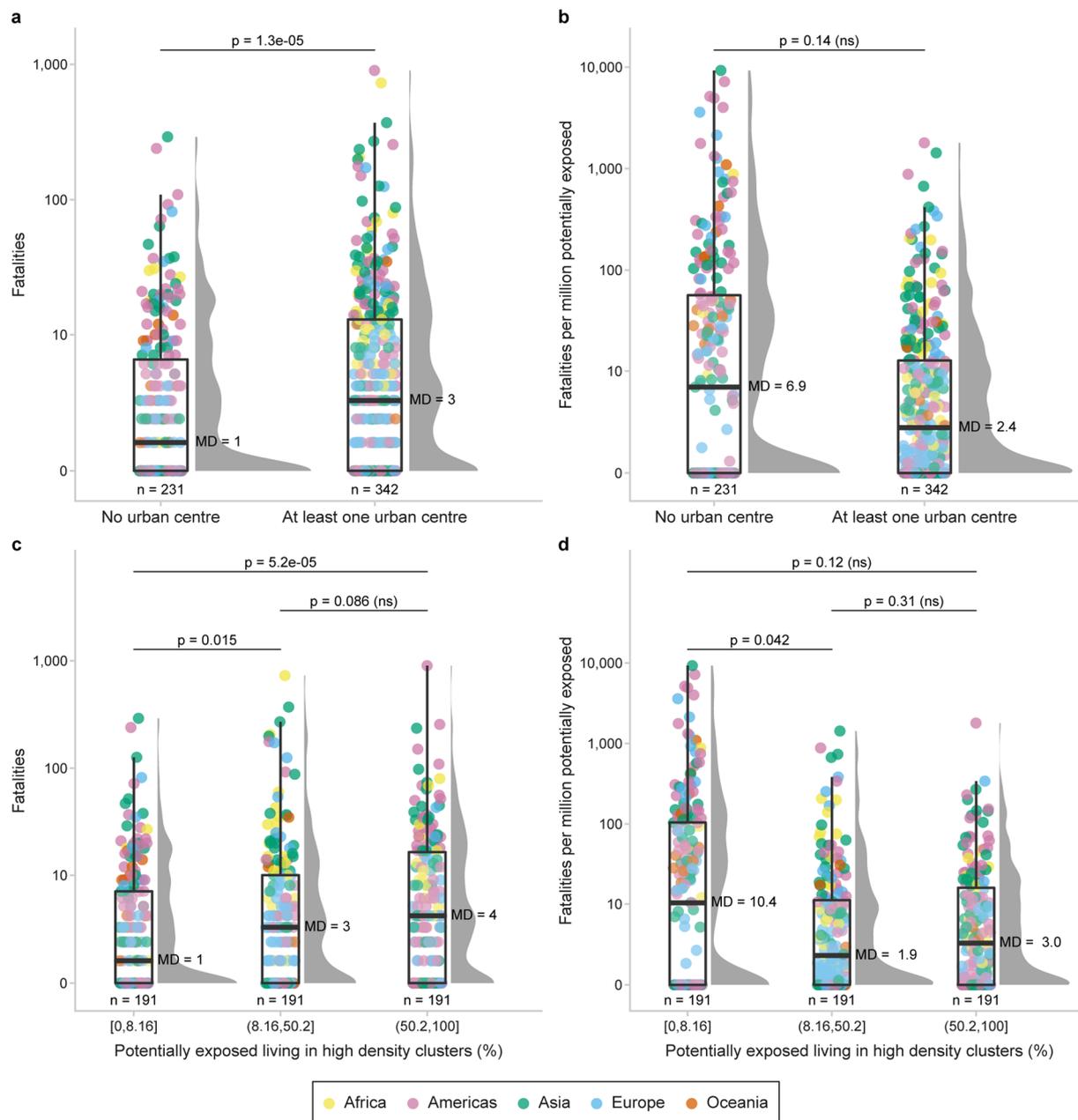
Extended Data Fig. 2 | Flood mortality and urbanity. This figure shows that flood disasters that affect regions with at least one major urban center generally result in higher absolute numbers of fatalities (**a**), but these urban events also result in lower mortality rates due to higher exposure estimates (**b**). The same pattern is visible when events are grouped according to the share of potentially exposed individuals living in high-density clusters (**c, d**), with each group containing a third of the sample. The dots indicate individual observations, the box hinges indicate the 25th and 75th percentiles, the centre lines indicate the median value (MD), and the whiskers indicate the interquartile range multiplied by a factor of 1.5. The P values refer to pairwise two-sided Wilcoxon tests comparing group means.

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Data collection	All data used in this analysis come from publicly available sources. The custom codes for the data collection, and the compiled datasheets, supporting the findings of this study are available in Zenodo with the identifier https://doi.org/10.5281/zenodo.7547323
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Ecological, evolutionary & environmental sciences study design

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Study description	We conduct quantitative statistical analyses on country level to evaluate if countries with high income inequality also tend to suffer more flood fatalities, compared to countries with low income inequality. We tested the association between income inequality and flood mortality at country level by combining data on disaster losses, human exposure and socioeconomic indicators from a number of international databases.
Research sample	The flood disaster reports and socioeconomic data are derived from existing datasets, as described in the paper. We only included records that had been geocoded on, at least, county or district level (or finer) by the database GDIS. This enabled usy to estimate the number of potentially exposed individuals for each record.
Sampling strategy	We included all samples that were available in the global and publacaly available databases.
Data collection	S.L. collected the data in 2022 from already published data sources, and compiled the variables of interest into one datasheet using R and Google Earth Engine.
Timing and spatial scale	Major floods occurring in middle- and high-income countries (MHICs) between 1990 and 2018 were included. As stated in the introduction, we limit the study to MHICs primarily due to comparability reasons and because we aim to shed light on the role of inequality in advanced economies.
Data exclusions	Only flood records geocoded to at least district level was included in the study, we thus exluded records geocoded to state level. The state level subdivisions are typically five times larger than the district subdivisions, which would have resulted in larger exposure estimates and hence potentially biasing the analysis. We also excluded one record as it did not contain any inhabitants according to the global population map, which we deemed unrealistic.

Reproducibility	Custom codes to replicate all tables, figures and results of this study are available in Zenodo with the identifier https://doi.org/10.5281/zenodo.7547323
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