Global mortality risk assessment from river flooding under climate change

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Abstract
Flooding that cause yearly economic losses and casualties have increased in frequency with global warming. Assessing the mortality risks of populations due to flooding is important and necessary for risk management and disaster reduction. Thus, this paper develops a method for assessing global mortality risks due to river flooding. Global historical annual death tolls are first estimated during the historical period 1986–2005 ($T_0$) by using available mortality vulnerability functions of river flooding. Then, the best vulnerability function is selected according to lower root mean square errors (RMSE) and the differences in the multi-year mean (DMYM) values. Next, the adjustment coefficient $K_c$ for each country (region) is calculated to use in the revision of the selected vulnerability function. Finally, the mortality risks are estimated based on an adjusted vulnerability function. As a case, the paper assessed and analysed the global mortality risks due to river flooding during 2016–2035 (2030s) and 2046–2065 (2050s) for the combined scenario of the Representative Concentration Pathway 4.5 (RCP4.5) and the Shared Socioeconomic Pathway 2 (SSP2), and the RCP8.5-SSP5 scenario. The results show that the estimation errors of the death tolls in most countries (regions) decrease after adjusting the vulnerability function. Under the current defense capacity and vulnerability level, the average annual death tolls of RCP4.5-SSP2 and RCP8.5-SSP5 in the 2030s will increase by 1.05 times and 0.93 times compared with the historical period. They will increase 1.89 and 2.20 times, respectively for the two scenarios during 2050s. High-risk areas are distributed in the south-eastern Eurasia.

1. Introduction
Flooding regularly causes severe casualties and great economic losses globally (Jongman \textit{et al} 2015, CERD and UNISDR 2018, CRED 2019), as well as a variety of horrible diseases and destruction of the ecological environment (Dionisio \textit{et al} 2017, Green \textit{et al} 2017, Berry \textit{et al} 2018). Moreover, losses due to floods have been increasing over the past several decades (Mohleji and Pielke 2014). River floods, in particular, are responsible for the largest proportion of total losses caused by floods (UNISDR 2011, Jongman \textit{et al} 2012).

Heavy rainfall is a major cause of river flood disasters. More frequent and heavier rainfall events have been observed around the world in recent decades (Gu \textit{et al} 2017a, Zhou and Wang 2017b). An increasing trend will continue in most regions later in the 21st century (Westra \textit{et al} 2013, Asadieh and Krakauer 2015, Donat \textit{et al} 2016). Although there is not abundant or sufficient evidence to suggest that increases in heavy rainfall would result in similar increases in streamflow (Wasko and Sharma 2017), there is a moderate level of confidence that increases in heavy rainfall will contribute to rain-generated local flooding in some catchments or regions (IPCC SREX 2012).
because of an accelerated global hydrological cycle (Roderick et al 2014). This implies a greater flooding hazard. In addition, an increasing number of populations and assets are exposed to flood hazards as socioeconomic development continues (Jongman et al 2012, 2015, Winsemius et al 2018, Liao et al 2019). Specifically, global urban land lying in low-elevation coastal zones will increase 230% from 2000 to 2030 (Güneralp et al 2015). Therefore, research on whether river flood risks will increase is essential and pressing, and is important to help humans adapt and cope with the impacts of climate change.

Flood risk is characterized by the combined consequences of flood hazards, exposure, and the vulnerability of social-economic objects (UNISDR 2011). The general method for determining river flood risk is to produce river flood hazards using hydrological models and inundation models based on precipitation data and then to combine the flood hazards with socioeconomic data to assess the affected population and the economic loss risks using certain algorithms (Hirabayashi et al 2013, Ward et al 2013, Winsemius et al 2013, Alfieri et al 2015, Arnell and Gosling 2016, Dottori et al 2016, Lim et al 2018, Wing et al 2018). In particular, many models have been produced to project future precipitation and social-economic information, including population and gross domestic product (GDP), under different scenarios present (IPCC AR5 2014). These data are provided as a basis for the comprehensive assessment of river flood risks under climate change. Most studies focus on both population and economic risks. There are proven vulnerability functions for the risk assessment of economic loss (Alfieri et al 2015, Muis et al 2015, Dottori et al 2016, Sarhadi et al 2016, Wing et al 2018). However, only exposed or affected populations are considered in the risk assessment of a population.

The reason that few studies focus on risks of loss of life is the lack of a proven vulnerability function for mortality risks. Several studies mentioned mortality risks from floods (Dilley et al 2005, Jongman et al 2015, Shi and Kaspersen 2015, Kinoshita et al 2018). Only Jongman et al (2015) and Kinoshita et al (2018) mentioned fatality vulnerability, which is a ratio of the observed flood fatalities to the population potentially affected. Jongman et al (2015) analyze the vulnerability at countries with different per capita GNP levels. Then they defined three vulnerability scenarios: ‘no additional adaptation’ (current vulnerability per income region remains unchanged), ‘medium adaptation’ (all countries converge to the current (1980–2010) average vulnerability by 2080) and ‘high adaptation’ (all countries converge to the current (1980–2010) average vulnerability level in high-income countries by 2080). Based on the three scenarios, future fatalities were estimated. Kinoshita et al (2018) developed an autonomous adaptation method to simulate the annual vulnerability by incorporating the variation trend of historical vulnerability and GDPs, for each country. However, in these works, vulnerability is indicated as an index, e.g. ratio of the observed flood fatality to the potentially affected exposure, without the consideration of inundation. Fatalities are usually caused by physical processes of flooding (inundation depth, flow velocity, fragmentation, collapse of buildings, etc.), as well as forecasting and evacuation governed by behavioral aspects, policies and decisions. Vulnerability-containing physical processes should take these determination elements into account. For example, Jonkman et al (2016) published a paper, the latest progress in life loss estimation, to review the methods used for life loss estimation and summarize the general characterizations (the applicable flood type and spatial detail level) of the methods. These methods summarized in Jonkman et al (2016) all considered at least one determination element of fatalities for floods. However, few of the methods are applicable and appropriate for global risk assessments because of the incompatible spatial scales of the models. Vulnerability index is more of a statistical concept while vulnerability function could reflect physical process to a certain extent. For the estimation of future death tolls to floods, only inundation extent is serviceable if using vulnerability index. Other information, such as inundation depth produced by hydrodynamic (or hydrological) models and flooding inundation model, is ignored.

It can be concluded that limited work has been completed on determining the risk of life loss due to flooding, especially work considering vulnerability and inundation depth. To address these gaps, this paper tried to develop a method for estimating future potential fatalities using vulnerability involving flooding inundation depth, and then to assess the mortality risk from river floods globally. Fatality vulnerability functions were developed for every country based on the existing vulnerability function. The death tolls were estimated to assess the mortality risk during 2016–2035 (2030s) and 2046–2065 (2050s) for the Representative Concentration Pathway 4.5 (RCP4.5)-SSP2 scenario and the RCP8.5-SSP5 scenario. This work can provide understanding of future disaster scenarios and scientific guidance for disaster reduction strategies.

2. Data and vulnerability functions

2.1. Data preparation

The main data used in the paper are shown in table 1. The main data used in the paper are shown in table 1. T0, 2030s and 2050s represent the time periods 1986–2005, 2016–2035 and 2046–2065, respectively.

The flood inundation datasets include inundation depth and fraction (i.e. ratio of flood-inundated area to total land area per grid cell; range, 0–1). They were
produced using daily runoff data to drive the hydrological model catchment-based macroscale floodplain (CaMa-Flood) simulations (Yamazaki et al 2011, Lim et al 2018) that integrate the global flood defense database FLOOD PROtection Standards (FLOPROS, Scussolini et al 2016). More information about data production is introduced in supplemental file (available online at stacks.iop.org/ERL/16/064036/mmedia). The inundation depth and fraction values were the annual maxima for the final dataset, which represents the worst scenario. Eleven Atmosphere-ocean Global Circulation Models (AOGCMs) were considered in the calculations (supplemental table 1). Specifically, the spatial resolution of the flood inundation level was high, and the level of protection was taken into account. For this dataset, large lake areas and abnormal depth values were masked to reduce the impact of outliers.

Population data included Gridded Population of the World (GPWv4) datasets and ISI-MIP population datasets. The GPWv4 datasets describe global population counts. The ISI-MIP population datasets contain historical and future estimates of the global grid population. For future population, the SSP2 and SSP3 scenario were selected to be combined with the RCP4.5 and RCP8.5 scenario, respectively. For more detailed data introduction please see supplemental file. The ISI-MIP population data was downscaled to 2.5′ × 2.5′ to be in accordance with the GPWv4 data (it was assumed that the distribution of the ISI-MIP population data at a 0.5° grid was similar to that of the GPWv4 data). The future population datasets were downscaled based on the GPWv4 data from 2015, and the historical population datasets were downscaled based on the GPWv4 data from 2000.

Historical disaster data from the Emergency Events Database (EM-DAT) were event-based and included information such as the time, location (country) and death toll of each event. This was currently the best publicly available global disaster data. Annual total deaths were calculated at country (region) unit. Supplemental figure 1 shows the spatial distribution of average annual deaths for T0 period.

### Table 1. The data used in this paper.

| Data                           | Temporal coverage | Scenarios/ version | Temporal resolution | Spatial resolution | Sources                          |
|-------------------------------|-------------------|--------------------|---------------------|-------------------|----------------------------------|
| Inundation                    | 2030s, 2050s      | RCP8.5             | 1 Year              | 2.5′              | Lim et al (2018)                 |
| ISI-MIP Population            | 2030s, 2050s      | SSP2               | 1 Year              | 0.5°              | Inter-Sectoral Impact Model      |
| Grided Population of the World| 2000, 2015        | v4                 |                     | 2.5′              | Socioeconomic Data Applications  |
| Basic geographic information data | —                | —                  | —                   | —                 | State Bureau of Surveying and Mapping, China |
| History disaster              | T0 (1986–2005)   | —                  | —                   | —                 | EM-DAT                           |

### 2.2. Available vulnerability functions

The fatalities caused by river floods were mainly determined by physical process of flooding, forecasting, evacuation and others (Brazdova and Riha 2013, Jonkman et al 2016). However, it is difficult to separate the individual contributions of these determinants to mortality and to consider multiple determinants for the vulnerability function, particularly at the global scale. In addition, as the inundation data were limited to annual maximal depth in an inundation grid, only depth could be used in the determination of risk assessment. Among existing studies, Duijer (1989) and Jonkman et al (2008) proposed the relation between inundation depth and population mortality (vulnerability function), which could be practicable for this paper. Duijer (1989) fitted a vulnerability curve (vulnerability function I) using data from a flood event that occurred in the Netherlands. Jonkman et al (2008) added other data from flood events occurring in the UK, Japan and Bangladesh and then divided the hazard zones into three types: breach zones, zones with rapidly rising water and remaining zones, after that three vulnerability curves were fitted in these three zones respectively. But the three zones could not be divided within a grid with a 2.5′ resolution. Considering that the remaining area is large area in the flood event, the paper only selects the vulnerability curve of the remaining zone as vulnerability function II. Vulnerability function I is shown in equation (1), and its curve is shown in figure 1(a). Vulnerability function II is shown in equation (2), and its curve is shown in figure 1(b).

\[
M(\text{dep}) = 0.665 \times 10^{-3} e^{1.16\text{dep}} \quad (1)
\]

where \( \text{dep} \) is the inundation depth \((m)\) in each grid and \( M(\text{dep}) \) is the mortality rate in each grid.

\[
M(\text{dep}) = \Phi \left[ \frac{\ln(\text{dep}) - 7.60}{2.75} \right] \quad \text{(2)}
\]

where \( \Phi \) is the cumulative normal distribution.
3. Methods to estimate future potential fatalities

Risk was defined as the combined consequences of flood hazard, vulnerability and exposure. Thus, in this paper, the mortality risk due to floods was calculated by equation (3).

\[
\text{death toll} = \text{hazard} \times \text{vulnerability} \times \text{exposure}. \quad (3)
\]

Figure 2 shows the technical flow chart outlining the method. It was separated into three parts: (a) calculating the historical annual death tolls for T₀ using all available mortality vulnerability functions and selecting the best one by analysing the RMSEs and DMYMs, (b) calculating the adjustment coefficient \(K_c\) and revising the selected vulnerability function at the country (region) level, and (c) calculating the future death tolls and analysing the risks.

3.1. Selection of vulnerability function

To select a more suitable vulnerability function, the annual death tolls of a grid with a 2.5\(^\circ\) × 2.5\(^\circ\) resolution were estimated for the T₀ period according to equations (4) and (5) using vulnerability functions I and II (in section 2.2), respectively (noted with result I and result II). Then, the estimated historical results were compared to the recorded death tolls. Given that the historical recorded death tolls from the EM-DAT were based on countries, this paper transformed the calculation results from the grid level to the country level. Next, the difference in multi-year mean (DMYM, equation (6)) values and the RMSE (equation (7)) values were both computed between the estimated death tolls (result I and result II) and the recorded deaths for the historical 20 years. The better vulnerability function was selected according to the lower DMYM and RMSE values.

\[
EDP_{\text{his}_i,j} = M(\text{dep}_{\text{his}_i,j}) \times \text{pop}_{\text{his}_i,j} \times \text{frc}_{\text{his}_i,j} \quad (4)
\]

\[
EDP_{\text{his}_i,j} = \frac{1}{11} \sum_{j=1}^{20} EDP_{\text{his}_i,j} \quad (5)
\]

where \(EDP_{\text{his}_i,j}\), \(\text{dep}_{\text{his}_i,j}\) and \(\text{frc}_{\text{his}_i,j}\) are the estimated death toll, inundation depth and inundation fraction for the \(i\)th AOGCM in the \(j\)th year of T₀ period, respectively; \(\text{pop}_{\text{his}_i,j}\) is the total population in the \(j\)th year of T₀ period; and \(EDP_{\text{his}_i,j}\) is the maximum death toll in the \(j\)th year, which was determined by taking the average of the results from the 11 AOGCMs in order to reduce the model uncertainties. The variable \(j\) represents the sequence number of years in the T₀ period.

\[
\text{DMYM} = \left| \frac{1}{20} \sum_{j=1}^{20} EDP_{\text{his}_c,j} - \frac{1}{20} \sum_{j=1}^{20} SDP_{\text{his}_c,j} \right| \quad (6)
\]

\[
\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{20} (EDP_{\text{his}_c,j} - SDP_{\text{his}_c,j})^2}{20}} \quad (7)
\]

where \(EDP_{\text{his}_c,j}\) and \(SDP_{\text{his}_c,j}\) are the estimated death toll and the recorded death toll for country \(c\) in the \(j\)th year of T₀ period, respectively.

Figure 3 shows the DMYM and RMSE comparison of the calculated results of the two vulnerability functions. Only countries (regions) with a historical death toll greater than 0 were calculated and showed. Lower DMYM and RMSE values represent better results. Thus, the paper chose vulnerability function II for the countries (regions) at the right of line \(y = x\) (DMYM II < DMYMI, RMSE II < RMSE I).
Figure 2. Research flow chart for calculating the global mortality risk from river flooding under climate change.

Figure 3. The DMYM and RMSE comparison of the calculated results that were calculated by two vulnerability functions. (a) Is the comparison of DMYM I and DMYM II for each country (region). DMYM I is the DMYM between historical estimation result I and the recorded death tolls, and DMYM II is the DMYM between historical estimation result II and the recorded death tolls. The values of DMYM I and DMYM II and their comparison are shown in supplemental table 2. (b) Is the comparison of RMSE I and RMSE II for each country (region). RMSE I is the RMSE between historical estimation result I and the recorded death tolls. RMSE II is the RMSE between historical estimation result II and the recorded death tolls. The RMSE values are shown in supplemental table 3.

There are 15 countries (regions) with DMYM I < DMYM II in figure 3(a). According to supplemental table 4, it can be found that these countries are almost all coastal or island countries (regions) with narrow land areas, distributed in eastern Asia, western Europe, and southern North America around the Caribbean Sea. There are 14 countries (regions) with RMSE I < RMSE II in figure 3(b). According to supplemental table 5, except for Canada and three inland countries in Central Europe, all other countries (regions) are coastal or island countries (regions) with narrow land areas.
countries (regions) are coastal or island countries (regions) with narrow land areas. According to the DMYM and RMSE values, vulnerability function I performs better than vulnerability function II for them. But, the two indicators are overall descriptions of the whole T0 period. In fact, in terms of estimation death tolls per year for T0 period, missing existed in many years for result I while few years for result II. Thus, we also select vulnerability function II for these countries (regions).

3.2. Calculation of adjustment coefficients to revision of vulnerability function for every country

Although a vulnerability function was developed using death toll data from different flooding events occurring in different countries, diversity existed in the different countries such that the estimated death tolls varied in accuracy for the different countries. To reduce the error as quickly as possible, the adjustment coefficient of every country was computed and used to revise the vulnerability function. The process was as follows.

Using the results of section 3.1, adjustment coefficients were calculated according to equation (8) for the countries with both total recorded death tolls and total estimated death tolls above zero during the T0 period. For countries with total recorded death tolls equal to zero during T0 period, the adjustment coefficient used was the minimum of all calculated \( K_c \) values. For countries with total recorded death tolls greater than zero but total estimated deaths equal to zero, the adjustment coefficient used was the average of all calculated \( K_c \) values.

\[
K_c = \frac{\sum_{j=1}^{20} SDP_{his,c,j}}{\sum_{j=1}^{20} EDP_{his,c,j}} \tag{8}
\]

where \( K_c \) is the adjustment coefficient of country \( c \) and \( j \) represents the sequential number of the year in the T0 period.

The adjusted vulnerability function is shown in equation (9). Then, the historical death tolls estimated using the adjusted vulnerability function were compared with the results estimated using vulnerability function II using the standard deviation between the average annual recorded death tolls and the average annual estimated death tolls for the historical period.

\[
AdjM_c (dep) = K_c \times M (dep) \tag{9}
\]

where \( AdjM_c (dep) \) is the adjusted vulnerability function of country \( c \).

The adjustment coefficients \( K_c \) for each country (region) are shown in supplemental table 6. To show the effect of \( K_c \), the standard deviation are compared before and after adjusting (figure 4), signalled by SD_V and SD_AdjV respectively. Before adjusting, there are 80 (53%) countries (regions) with SD values larger than 50, 25 (17%) countries (regions) with SD values between 10 and 50, and 45 (30%) with SD values smaller than 10. After adjusting, the numbers of countries (regions) are 13 (9%), 45 (30%) and 92 (61%), respectively. The SD_AdjV values are lower significantly in 79% of all countries (regions) compared to the SD_V. Therefore, it can be considered that the improved vulnerability functions are satisfactory for most countries (regions).

3.3. Estimation of future potential fatalities

The same adjustment coefficient was assumed for all grids in the same country. Thus, the death toll of a grid with a \( 2.5' \times 2.5' \) resolution for a given year \( j \) during the future period in the country \( c \) was calculated by equations (10) and (11).

\[
\text{death toll}_{\text{fut},c,i} = AdjM_c \left( \text{dep}_{\text{fut},c,i} \right) \times \text{pop}_{\text{fut},c} \times \text{frc}_{\text{fut},c,i} \tag{10}
\]

\[
\text{death toll}_{\text{fut},c} = \frac{1}{11} \sum_{i=1}^{11} \text{death toll}_{\text{fut},c,i} \tag{11}
\]

where death toll_{fut,c,i}, dep_{fut,c,i} and frc_{fut,c,i} are the death toll, inundation depth and inundation fraction of the \( i \)th AOGCM, respectively; pop_{fut,c} is the total population; and death toll_{fut,c} is the death toll of a given grid in country \( c \) for a year, which was calculated as the average of all death toll values from the 11 AOGCMs to reduce the uncertainties of the models.

4. The case of mortality risk assessment of river flooding

Using the method above, this paper assessed the global mortality risks from river floods during 2016–2035 and 2046–2065 for the RCP4.5-SSP2 and RCP8.5-SSP5 scenarios, the average death tolls of these two future 20 years are presented as the death tolls of the 2030s and 2050s, respectively. The results are shown and analysed at the country (region) unit and are compared with existing results to reflect the effect of human adaption.

4.1. Projected potential flood consequences and the change relative to historical period

Statistically, the global average annual death toll due to river floods was 5.1k persons during T0 period. At the current defense capacity and vulnerability level, it will be approximately 10.5k persons for the RCP4.5-SSP2 scenario and 9.9k persons for the RCP8.5-SSP5 scenario during the 2030s; increasing 1.05 and 0.93 times, respectively, compared with the T0 period. It will be approximately 14.8k persons for the RCP4.5-SSP2 scenario and 16.4k persons for the
Figure 4. The comparison of SD_V and SD_AdjV. (a) Is the standard deviation between recorded death tolls and estimated death tolls without adjusting the vulnerability function (SD_V). (b) Is the standard deviation between recorded death tolls and estimated death tolls using adjusted vulnerability functions (SD_AdjV). (c) Shows the number of countries (regions) for every SD grade. The values of SD_V and SD_AdjV are showed in supplemental table 7. For (a) and (b), red color represents the largest grad of SD and blue color represents the lowest grad; the countries (regions) filled with black spots have smaller error after adjusting vulnerability functions than before adjusting (SD_AdjV < SD_V).

RCP8.5-SSP5 scenario during the 2050s, increasing 1.89 and 2.20 times, respectively, compared with the T0 period.

Figure 5 shows the spatial distribution of the potential average annual death tolls at the country (region) unit. There is no obvious spatial variability for different time periods. During the 2030s, high-risk countries (regions) (death toll > 500 persons) accounted for 1.26% of the total number of countries (regions), located in eastern and southern Asia, including India, China and Bangladesh. Medium-risk countries (regions) (death toll between 10 and 500 persons) account for 15.97% for RCP4.5-SSP2 and 16.39% for RCP8.5-SSP5 of the total number of countries; the medium-risk countries (regions) are all coastal countries such as Indonesia, Thailand, Pakistan, Iran, Brazil, and Mozambique. During the 2050s, high-risk countries (regions) are predicted to account for 2.10% of the total number of countries; these countries are distributed in East Asia, South Asia and Southeast Asia, including China, India, Bangladesh, Pakistan and Indonesia. Pakistan and Indonesia change from the medium-risk grade to the high-risk grade with the change in the time period from the 2030s to the 2050s. Medium-risk countries occupy 18.91% for RCP4.5-SSP2 and 17.65% for RCP8.5-SSP5 of the total number of countries. These high-risk countries are almost all coastal counties, such as Iran, Thailand, Australia, the United States, Brazil, and Columbia.

Figure 6 shows the increase trends of mortality risks relative to the T0 period due to river flooding in the country (region) units. The areas with increasing trends are mainly distributed in southern Eurasia, Southeast Asia, the coast of Africa, Australia, North America and southern South America near the equator. During the 2030s, there are 8 countries (regions), 3.36% of the total number of countries, with high predicted growths of risks (the growth of the death toll > twice). They include Indonesia, East Timor, the United States, Bangladesh, Angola, Mozambique, Poland and Greece. There are five countries (regions) occupying 2.10% for the RCP8.5-SSP5 scenario, with high predicted growths of risks. They include East Timor, Ecuador, the United States, Bangladesh and...
Indonesia. During the 2050s, there are 21 countries (regions) for the RCP4.5-SSP2 scenario and 23 countries (regions) for the RCP8.5-SSP5 scenario with high growth of risks, 8.82% and 9.66% of the total number of countries respectively. They are almost coastal countries (regions). India, Australia, Peru, Ecuador, Columbia and Niger change from low-growth to high-growth grades from the 2030s to the 2050s.

4.2. Uncertainties
The results of risks were calculated using 11 AOGCMs. And the results of figure 5 were multi-model mean. In order to measure the uncertainties
of models, we applied coefficient of variation (CV), which divides the standard deviation by mean value. In this way, comparison could be made in different countries (regions). Figure 7 shows the spatial distribution of CV. The countries (regions) with larger uncertainties are mainly concentrated in the west of Eurasia, in addition, also including Guinea and Senegal (located in the west coast of Africa), and Japan (an island nation located in eastern Asia). It is under the RCP8.5-SSP5 scenario for 2050s that the uncertainties are larger than other scenarios on the whole.

4.3. Effect of adaption
To verify the rationally of the results, we compare the results of this paper with the work of Kinoshita et al (2018). Both studies calculated flood inundation by using the same runoff dataset and CaMa-Flood model, including the RCP4.5-SSP2 scenario for 2016–2035 and 2046–2065 periods. Figure 8 shows the results of Kinoshita et al (2018). For the RCP4.5-SSP2 scenario, the average annual death toll during the 2030s is predicted to be approximately 10.5k persons in this paper, while it is approximately 7k persons in figure 8. The death toll is predicted in this paper to be approximately 14.8k persons during the 2050s, while it is approximately 5k persons in figure 8.

The main reason for these differences is that, this study assumes the coping capacity and vulnerability are at the current level, while figure 8 considered autonomous adaptation of future vulnerability in which vulnerability declines with increasing GDP in the future. Thus, the differences reflect the effects of adaption to floods under climate change. The reduction in vulnerability would reduce the number of global deaths by approximately 3.5k persons in 2030s and approximately 9.8k persons in 2050s, respectively.

5. Conclusion and discussion

5.1. Conclusion
In this paper, a method was developed for assessing the global mortality risks from river flooding using adjusted vulnerability functions. As a case, the paper assessed the mortality risks during the 2030s and 2050s for the RCP4.5-SSP2 and RCP8.5-SSP5 scenarios. First, based on the two mortality vulnerability functions in previous studies, historical annual
death tolls are estimated during T0 period. Then, the best vulnerability function is selected according to the RMSEs and DMYMs. Next, adjustment coefficient \( K_c \) was calculated for each country (region) to revise the selected vulnerability function. Finally, the mortality risks are estimated using an adjusted vulnerability function. The results show that adjusted vulnerability functions have decreased errors when estimating the death toll at the country unit. At the current defense capacity and vulnerability level, the average annual death tolls will increase 1.05 times for the RCP4.5-SSP2 scenario and 0.93 times for the RCP8.5-SSP5 scenario during the 2030s compared with the historical period. They will be increase 1.89 and 2.20 times, respectively for the two scenarios during 2050s. High-risk areas are distributed in south-eastern Eurasia.

5.2. Limitation of method

It is worth noting that this study tried to estimate future fatalities from floods using vulnerability functions considering inundation depth rather than the vulnerability indicator. The development of the adjusted mortality vulnerability function at the country (regional) unit addresses the issue of having only one global vulnerability function. Additionally, the death toll is estimated rather than the population affected by river flooding, which addresses the gap that arises when using an indicator (death toll) in population risk assessments. Of course, it is expected that more flooding information could be considered in mortality risk assessment so that more physical process can be also considered in next studies. These studies are important to help humans understand the danger of future river flooding, so as to adapt to and cope with the impacts of climate change.

Further improvements of the method used in this study are possible.

(a) Adjustment coefficient \( K_c \) is influenced by recorded historical deaths. When recorded deaths are lower than real values, \( K_c \) is underestimated, which leads to underestimation of risks. Conversely, \( K_c \) is overestimated leading to overestimation of risks. For those countries (regions) with no recorded deaths, \( K_c \) is the average or minimum of other countries (regions). It may also lead to an overestimation or underestimation of risk. The recorded deaths data are from EM-DAT, which is currently the best publicly available global dataset, although maybe there are missing data. According to the criteria of data collection, missing a few slight disasters events has very little effect on the total death tolls of a years for a country. Of course, a few countries may not report heavy deaths from floods due to varieties of reasons during 1986–2005. The \( K_c \) should be determined using data from some years during 1986–2005 to estimate the death toll, which will then be verified by using the data of the remaining years. However, due to limited loss data for the short period, all data were used in the calculation of the coefficient \( K_c \) in this study.

(b) The vulnerability function (equation (2)) represents the vulnerability of historical period. In the future, as vulnerability decreases, the mortality rate will decrease corresponding to the same inundation depth. But this is not considered in this study. Therefore, in the following research, the impact of GDP development on vulnerability function should be included in order to deal with this limitation.

Data availability statement

ISI-MIP Population data is available at http://clima-dods.ictp.it/Users/fcolon_g/ISI-MIP/. Grid-ded Population of the World data is available at https://sedac.ciesin.columbia.edu/data/collection/gpw-v4. History disaster data is available at https://public.emdat.be/. The flood inundation data is available by emailing us.

The data that support the findings of this study are available upon reasonable request from the authors.

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