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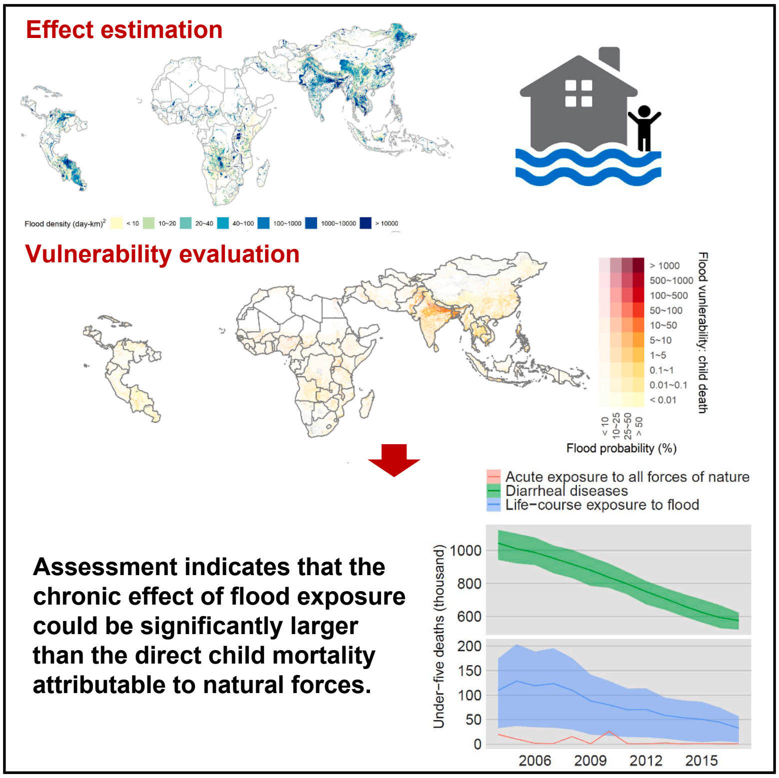
Flood exposure contributes to under-five mortality in low- and middle-income countries

Graphical abstract



Highlights

- Life-course exposure to flood increases odds of child mortality
- Long-term flood exposure contributed to 33,000 under-5 deaths across 100 LMICs
- Regional policies to reduce vulnerability to flood can improve child health

Authors

Pengfei Li, Mingkun Tong, Jingyi Wu, ..., Xiaofei Sun, Jiwei Li, Tao Xue

Correspondence

jiwei_li@zju.edu.cn (J.L.),
txue@hsc.pku.edu.cn (T.X.)

In brief

Flooding is one of the most prevalent natural disasters worldwide, which can have long-term indirect effects on child health. This study presents the first assessment of <5-year-old deaths (U5Ds) attributable to long-term flood exposure in 100 low- and middle-income countries, which was found to be dramatically higher than acute U5Ds attributable to all forces of nature. The vulnerable communities identified in this study can help plan relevant climate-health services and public health interventions.

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Flood exposure contributes to under-five mortality in low- and middle-income countries

Pengfei Li,[1,2,3,8] Mingkun Tong,[1,8] Jingyi Wu,[2] Xia Meng,[4] Xinguang Fan,[5] Xiaofei Sun,[6] Jiwei Li,[6,*] and Tao Xue[1,2,7,8,9,*]

[1]Institute of Reproductive and Child Health, National Health Commission Key Laboratory of Reproductive Health and Department of Epidemiology and Biostatistics, Ministry of Education Key Laboratory of Epidemiology of Major Diseases (PKU), School of Public Health, Peking University Health Science Center, Beijing 100191, China

[2]Advanced Institute of Information Technology, Peking University, Hangzhou 311215, China

[3]School of Nursing, Peking University, Beijing 100191, China

[4]School of Public Health, Key Laboratory of Public Health Safety of the Ministry of Education, and Key Laboratory of Health Technology Assessment of the Ministry of Health, Fudan University, Shanghai 200433, China

[5]Department of Sociology, Peking University, Beijing 100871, China

[6]School of Computer Science, Zhejiang University, Hangzhou 310058, China

[7]State Environmental Protection Key Laboratory of Atmospheric Exposure and Health Risk Management, Center for Environment and Health, Peking University, Beijing 100871, China

[8]These authors contributed equally

[9]Lead contact

*Correspondence: jiwei_li@zju.edu.cn (J.L.), txue@hsc.pku.edu.cn (T.X.)

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SCIENCE FOR SOCIETY Global warming and rapid urbanization are intensifying extreme weather events like heavy rainfall and rising sea levels, leading to more frequent and severe floods. In low- and middle-income countries (LMICs), floods compound pre-existing high child mortality. While the immediate deaths caused by floods are visible and tragic, the long-term health impacts on vulnerable children are less obvious and often overlooked by both the public and policymakers. The long-term effects of floods on vulnerable children in LMICs remain poorly understood. This study estimates that 33,000 under-5 deaths in 2017 across 100 LMICs were attributable to long-term flood exposure, a number significantly higher than the acute deaths caused by all natural forces combined. This work highlights the substantial long-term health impacts of floods on vulnerable children and provides a scientific database to inform regional policies to reduce flood vulnerability and improve child health in LMICs.

SUMMARY

Flood, a natural disaster closely related to global climate change, harms child health. However, the long-term effect of flood exposure on child mortality is unknown, particularly in low- and middle-income countries (LMICs). Here, based on a sibling-matched case-control design and exposure data of 913 large flood events, we first estimate the under-5 deaths (U5Ds) attributable to long-term flood exposure in 100 LMICs, where there are >90% of global U5Ds. We find that, in 2017, in the 100 LMICs, 26.4% of children <5 years of age were exposed to flood at least once during their life course, which was associated with 33,000 (95% confidence interval [CI] 4,000, 57,000) premature deaths. The chronic effect could be significantly larger than direct child mortality attributable to natural forces (i.e., 832 [95% CI 806, 856] U5Ds). The long-term health impacts of floods are nonnegligible, and the vulnerable communities identified in this study can help plan relevant climate-health services and public health interventions.

INTRODUCTION

Flooding is one of the most prevalent natural disasters worldwide. In 2022, the Emergency Event Database (EM-DAT) recorded 176 flooding events out of 387 natural hazards and disasters worldwide.[1] Nearly 19% of the world population (i.e., 1.47 billion) is directly exposed to once-in-a-century flood events.[2] Of this section of the global population, 89% live in low- and middle-income countries (LMICs). Such countries have poorly developed infrastructure, such as drainage, which can amplify flood risk and damage.[3,4] In the future, extreme precipitation and sea level rise caused by global warming, land degradation, and rapid urbanization, are expected to increase the frequency and intensity of floods globally.[5] For instance, 1.5°C warming will increase the incidence of flood hazards due to increased surface flows in southern Asia, Southeast Asia, and Central Africa.[6] According to a report in the United States, climate change will result in a 20% increase in the magnitude of, and a >200% increase in the frequency of, extreme rainfall events, leading to a 30%–127% increase in the number of people exposed to floods.[7]

Children are vulnerable to natural disasters, including floods,[8] because their nervous systems, immune responses, physical development, and behavior are immature.[9] For instance, the physiological characteristics of children, such as higher surface-to-mass ratios and less fluid in their bodies, contribute to an elevated health risk from the fluid and body heat loss after flood exposure, and result in an increased risk of mortality.[9] Indeed, small and moderate natural disasters have profound effects on child health by increasing the risk for acute illnesses, such as diarrhea, fever, and acute respiratory infection, which are the most common causes of child death in LMICs due to the immature immune response.[10,11] In addition, children have limited ability to recover from difficult situations. They are easily affected by mental stresses, such as anxiety, fear, and isolation. For instance, posttraumatic stress disorder (PTSD) symptoms are prevalent among children, due to the trauma experienced during natural disasters,[12] and the mental stresses of children have been associated with less favorable levels of biomarkers and elevated risk of premature mortality.[13]

As well as direct effects, flood exposure can have long-term indirect effects on human health via environmental and socioeconomic pathways. During and after severe floods, life-supporting services, such as water, sanitation conditions, and basic medical services, are disrupted. Without water and sanitation, fecal-oral and vector-borne diseases (e.g., diarrhea and malaria) are prevalent[14]; these are associated with an increased risk for child mortality. Furthermore, the effect of flood exposure on mental health and socioeconomic status (e.g., economic loss, migration, and PTSD) can result in chronic subclinical outcomes, such as malnutrition, stunting, and wasting,[15] which, in the long term, adversely affect the survival rate during childhood.[16,17] However, most studies of the association between floods and child mortality have focused on short-term effects.[18,19] Compared with direct deaths (e.g., caused by drowning and fatal injuries) immediately after flood exposure, the long-term indirect effects on child mortality can be overlooked, easily ignored by the public and policymakers, and difficult to detect because of complex confounders. To evaluate the burden of disease, assessment on the association between long-term flood exposure and child mortality is needed. In addition, as a key pathway in the climate-health nexus, to what degree the flood exposure affects the health of vulnerable children is unknown. To improve climate resilience, the knowledge gap needs to be filled.

The burden of child mortality attributable to floods could vary by sociodemographic characteristics, the crucial factors in vulnerability assessment. First, because there are multiple indirect pathways underlying the relationship between flood exposure and a long-term outcome, the effect is heterogeneous between individuals. For instance, young age, female sex, minority, and low socioeconomic status enhance susceptibility to floods.[10,20] Second, floods can affect individuals with different levels of baseline health differently. For instance, children in residential areas of temporary or unstable housing, who usually exhibit a relatively poor health condition (a relatively high mortality), face an elevated risk of sustaining irreversible injuries during floods and experience greater challenges in recovery,[21] compared with those in well-designed cities. Finally, susceptibility and poor health at baseline can interact, given the complex feedback between natural forces and socioeconomic development. For example, people experiencing poverty are more likely to live on a flood plain or close to coastal regions prone to flooding.[22] Therefore, information on the spatial distribution of vulnerable subpopulations is needed to plan interventions against flood-associated diseases. Although the health effect of flood has been investigated by local studies, the global impacts from flood on child mortality is unknown due to many difficulties, including heterogeneity in the effect of flood, and complexity embedded in spatiotemporal variation of flood exposure.

Here we investigated the overall and subpopulation-heterogeneous association between flood exposure (I/E) and child mortality (O) among children <18 years of age from LMICs (P), compared with those unexposed to flood (C), in a sibling-matched case-control study. The associations were expanded in 100 LMICs, which covered >90% of global <5-year-old deaths (U5Ds), to obtain a globally representative estimate of U5Ds attributable to long-term flood exposure. We also investigated the vulnerability of children to flood in the 100 LMICs. Our study reveals the nonnegligible long-term health impacts of flood on vulnerable children and regional policies to reduce vulnerability to floods are needed to improve child health in LMICs. By identifying communities that are vulnerable to flooding, we provide a scientific database to inform the planning of relevant climate-health services.

RESULTS

Methods summary

This sibling-matched case-control study analyzed 168,762 deaths of children (<18 years of age) in 55 LMICs from 2000 to 2018, using data from Demographic and Health Surveys (DHSs). Each deceased child was matched with their sibling(s), and a weighted approach was used to equalize the sample sizes. We assessed flood exposure as the presence of a satellite-detected flooded area within 10 km of the residence during the life course using the Global Flood Database. The association between flood exposure and child mortality was evaluated by conditional logit regression. We explored heterogeneity in the association by stratification according to sex, age, and socioeconomic status (indicated by satellite nightlight). The strata-specific associations between life-course flood exposure and child death were applied to characterize flood vulnerability, and to assess flood-attributable deaths among children in 100 LMICs, which accounted for >90% of all <5-year-old deaths globally.

Descriptive statistics

A global product mapped 913 large flood events from 2000 to 2018 (Figure 1). We assessed flood exposure across 55 LMICs based on 294 of these events. The spatial distribution of flood

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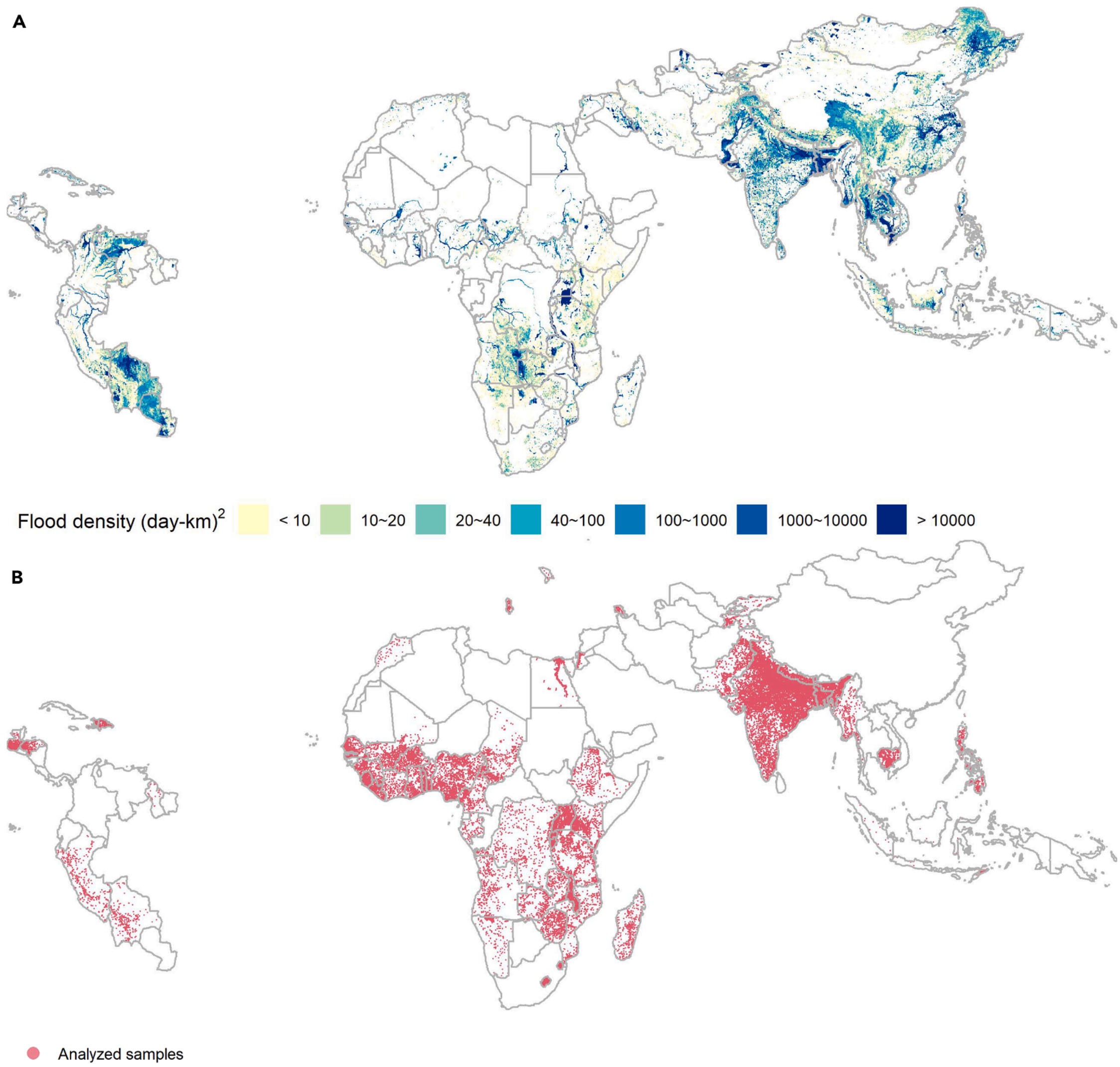

Figure 1. Spatial distribution of flood density across the 100 low- and middle-income countries and locations of analyzed children
(A) The flood density quantified as the sum of flood duration (day) and area (km^2) per pixel of a regular $0.1^\circ \times 0.1^\circ$ grid over the period of 2000–2018.
(B) The locations of analyzed children.

hotspots coincided with areas of surface water. A portion of the analyzed samples was distributed across several identified flood hotspot regions, such as the North Indian River Plain and human settlements neighboring Lake Victoria, Lake Malawi, Nile River, Niger, Mekong River, and Lake Titicaca. We identified 477,669 children, among whom 168,762 (35.3%) died from 2000 to 2018 (Table S1). The population characteristics of cases and their weighted matched controls are shown in Table 1. Of those cases, 2.4%, 9.8%, and 13.6% experienced at least one flood event during the month of death (short-term), the 10 months preceding death (middle-term), or the whole life course (long-term), respectively. The mean survival duration of the cases was 9.9 months (interquartile range 0.0–12.0 months).

Association between flood exposure and child mortality

Flood exposure at least once during the life course significantly increased child mortality, which remained significant after adjustment for multiple potential confounders and random effects (Figure 2A). According to the fully adjusted model, long-term exposure to flood was associated with a 2.82% (95% confidence interval [CI] 0.50%, 5.19%) increment in child mortality. After further adjusting for heterogeneity (Figure 2A), the average effect of life-course flood exposure increased to 4.44% (95% CI 1.59%, 7.37%). The association between flood exposure and child mortality was sensitive to different time windows of exposure. No significant association was observed for short- or medium-term exposure. We created alternative variables of flood exposure using different spatial buffers and re-ran the fully adjusted models. The 10-km buffer was appropriate for capturing the medium- and long-term effects of flood (Figure 2C). Furthermore, we parameterized flood exposure as a distributed lag term using cross-basis functions and explored the lagged effect by age group. A time window >10 months preceding occurrence of the health outcome was sufficient to

Table 1. Population characteristics of cases and their weighted matched controls

	Sample size (percentage %) or mean (interquartile range)		
	Case-control pair	Weighted case	Weighted control
Total	168,762 (100)	84,381 (100)	84,381 (100)
Short-term exposure (1 month)	4,032 (2.4)	2,017 (2.4)	2,015 (2.4)
Middle-term exposure (10 months)	16,357 (9.7)	8,288 (9.8)	8,069 (9.6)
Long-term exposure (life course)	22,715 (13.5)	11,474 (13.6)	11,241 (13.3)
Length of survival, months	9.9 (0.0–12.0)	9.9 (0.0–12.0)	9.9 (0.0–12.0)
Region			
Africa, Europe, & Central Asia	106,820 (63.3)	53,410 (63.3)	53,410 (63.3)
East Asia & Pacific	6,526 (3.9)	3,263 (3.9)	3,263 (3.9)
Latin America & Caribbean	6,720 (4.0)	3,360 (4.0)	3,360 (4.0)
South Asia	48,696 (28.9)	24,348 (28.9)	24,348 (28.9)
Sex			
Male	87,991 (52.1)	45,609 (54.1)	42,382 (50.2)
Female	80,771 (47.9)	38,772 (45.9)	41,999 (49.8)
Residence			
Urban	36,878 (21.9)	18,439 (21.9)	18,439 (21.9)
Rural	131,884 (78.1)	65,942 (78.1)	65,942 (78.1)
Birth			
Singleton	157,551 (93.4)	76,452 (90.6)	81,099 (96.1)
Multiple births	11,211 (6.6)	7,929 (9.4)	3,282 (3.9)
Mother's parity status			
Nulliparous	28,623 (17.0)	18,112 (21.5)	10,511 (12.5)
Multiparous	140,139 (83.0)	66,269 (78.5)	73,870 (87.5)
Maternal body mass index			
Underweight	18,262 (10.8)	9,131 (10.8)	9,131 (10.8)
Healthy	72,386 (42.9)	36,193 (42.9)	36,193 (42.9)
Overweight	18,080 (10.7)	9,040 (10.7)	9,040 (10.7)
Obese	6,916 (4.1)	3,458 (4.1)	3,458 (4.1)
Unknown	53,118 (31.5)	26,559 (31.5)	26,559 (31.5)
Maternal education			
No education	84,866 (50.3)	42,433 (50.3)	42,433 (50.3)
Primary	52,172 (30.9)	26,086 (30.9)	26,086 (30.9)
Secondary	28,514 (16.9)	14,257 (16.9)	14,257 (16.9)
Higher	3,208 (1.9)	1,604 (1.9)	1,604 (1.9)
Unknown	2 (0.0)	1 (0.0)	1 (0.0)
Mother's smoking status			
Never smoker	132,708 (78.6)	66,354 (78.6)	66,354 (78.6)
Smokers	13,048 (7.7)	6,524 (7.7)	6,524 (7.7)
Unknown	23,006 (13.6)	11,503 (13.6)	11,503 (13.6)
Mother's employment status			
Employed	86,804 (51.4)	43,402 (51.4)	43,402 (51.4)
Unemployed	38,284 (22.7)	19,142 (22.7)	19,142 (22.7)
Unknown	43,674 (25.9)	21,837 (25.9)	21,837 (25.9)
Sex of household head			
Male	140,054 (83.0)	70,027 (83.0)	70,027 (83.0)
Female	28,708 (17.0)	14,354 (17.0)	14,354 (17.0)
Wealth			
Poorest	55,176 (32.7)	27,588 (32.7)	27,588 (32.7)
Poorer	42,350 (25.1)	21,175 (25.1)	21,175 (25.1)

(*Continued on next page*)

Table 1. *Continued*

	Sample size (percentage %) or mean (interquartile range)		
	Case-control pair	Weighted case	Weighted control
Middle	32,322 (19.2)	16,161 (19.2)	16,161 (19.2)
Richer	24,368 (14.4)	12,184 (14.4)	12,184 (14.4)
Richest	14,476 (8.6)	7,238 (8.6)	7,238 (8.6)
Unknown	70 (0.0)	35 (0.0)	35 (0.0)
Type of cooking energy used			
Unclean	146,838 (87.0)	73,419 (87.0)	73,419 (87.0)
Clean	16,746 (9.9)	8,373 (9.9)	8,373 (9.9)
Unknown	5,178 (3.1)	2,589 (3.1)	2,589 (3.1)
$PM_{2.5}$ ($\mu g/m^3$)[a]	29.9 (11.0–39.7)	29.7 (10.9–39.4)	30.1 (11.0–40.0)
Nightlight (digit-number)	6.8 (0.0–6.0)	6.7 (0.0–6.0)	6.9 (0.0–7.0)

[a]The numerical variables are presented as mean and interquartile range; and the rest are categorical variables, presented as sample size and percentage.

capture the lagged effect of flood. The lag pattern could explain why increased risk of child mortality was positively associated with medium- or long-term, but not short-term, exposure in the main models (Figure 2A).

The heterogeneity in the association was confirmed by examining the interaction between flood exposure and a subpopulation indicator (Figure S2). Using a fully adjusted model with interactions, the estimated effect of life-course flood exposure was significantly modified by sex, residence (urban vs. rural), and maternal parity status. In addition, an age-specific lagged effect suggested that the effect of flood varied according to life stage. To reduce complexity, we ignored maternal parity, because this factor is not typically available for risk assessment in the general population. In addition, we replaced residence with a continuous variable, satellite nightlight, to characterize socioeconomic development. Finally, we evaluated heterogeneity using a random slope of flood exposure, which parameterized the effect as a function varying by sex, age, and nightlight at the residence (Figure 2B). Children $\geq$5 years of age were more susceptible to the effects of long-term flood exposure, compared with those <5 years of age. Girls were more susceptible than boys, for all age groups except for newborns. Among <5-year-old children, socioeconomic development (as indicated by increased nightlight brightness) might lower the susceptibility. By contrast, socioeconomic development significantly increased susceptibility among children $\geq$5 years of age.

Vulnerability and probability of flood exposure

The between-individual variation in the heterogeneous effect of flood and in baseline mortality rate resulted in differential vulnerabilities to flood exposure. Therefore, the effect of flood on child mortality was co-determined by vulnerability and probability of flood exposure (Figure 3A).

From 2000 to 2017, the children-number-weighted frequency of flooded years was 23%, suggesting that flooding occurred at least annually. Based on the 2017 population, 16%, 7%, or 1% of children lived in an area with a flood probability of >50%, >75%, or >95%, respectively. The sex-age structures were similar among areas with different flood probabilities and rarely flooded (probability <$\sim$25%) or frequently flooded (>75%) areas tended to have low socioeconomic statuses (Figure 3B). Across the study domain, most frequently flooded areas were in central and southern Asia (CSA), and vulnerable individuals (>0.5 deaths per 1,000 children) in rarely or frequently flooded areas were clustered in Sub-Saharan Africa and CSA, respectively (Figure 3C). As a result of the co-incidence of high vulnerability and high probability of exposure, the mortality burden attributable to floods is disproportionally distributed in CSA (particularly in populous India, Pakistan, and Bangladesh).

The effects of a flood on health depend on its location. Based on the 2017 real-world exposure and population, in terms of county-level average, the excess deaths per 1,000 exposed children associated with life-course flood exposure varied from -0.46 (95% CI -1.9, 0.53) in Eritrea to 1.00 (95% CI 0.54, 1.53) in Yemen. For populous countries, such as Pakistan, Nigeria, India, Bangladesh, and China, the effects were estimated to be 0.38 (95% CI 0.13, 0.57), 0.32 (95% CI 0, 0.57), 0.27 (95% CI 0.1, 0.41), 0.26 (95% CI 0.04, 0.44), and 0.11 (95% CI 0.03, 0.18), respectively. Because vulnerability to flood varies geographically, a gridded assessment based on high-resolution inputs is needed to characterize the effects of flood exposure on health.

Burden of child mortality attributable to flood

To explore the spatiotemporal variation in flood-related child mortality, we estimated the attributable deaths of <5-year-old children (Figures 4, S3, and S4; Table S2). In 2004, 42.0% of children born from 2000 to 2004 were exposed to flood at least once. The life-course exposure was associated with 110,000 (95% CI 33,000, 174,000) U5Ds, accounting for 1.34% of all U5Ds in the 100 LMICs. Across the study domain, the fraction of exposed children decreased to 41.6% in 2010, and to 26.4% in 2017; the number of attributable U5Ds decreased to 80,000 (95% CI 17,000, 129,000) in 2010, and to 33,000 (95% CI 4000, 57,000) in 2017. The decline in the burden of flood-associated U5Ds might be a result of improvement of the lower baseline U5D rate, decrease in the proportion of exposed children, and attenuation of flood effects due to socioeconomic development (i.e., a weaker flood-U5D association in brighter nightlight areas; Figure 2B).

The burden of flood-associated U5Ds was highly spatially clustered (Figure 4), particularly in CSA, which accounted for

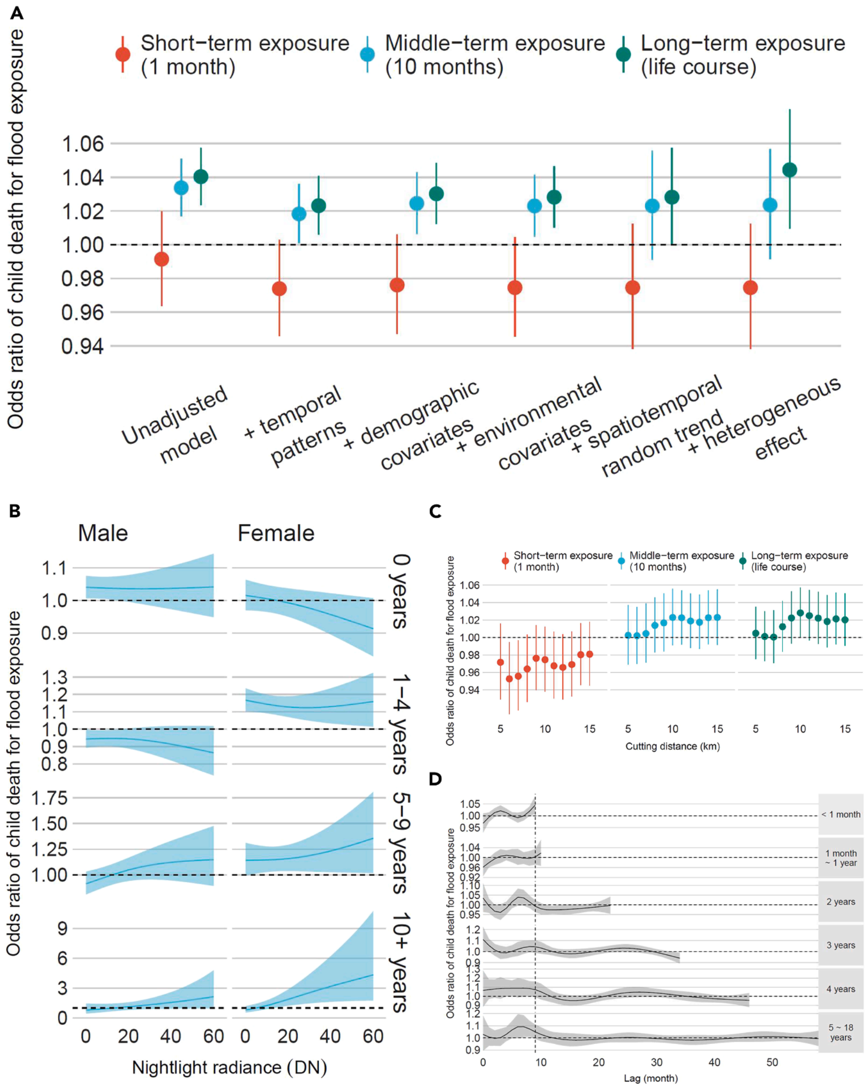

Figure 2. The estimated associations between flood exposure and child mortality

(A) The linear results from models with different adjusted covariates.

(B) Modifications on the association by age, sex, and nightlight.

(C) The associations estimated by different buffers for exposure assessment.

(D) The estimates from distributed lag models by age groups. For (A), temporal patterns denoted for the spline terms for year and month; demographic covariates included child sex, singleton or multiple birth, and birth order; environmental covariates included $PM_{2.5}$ and nightlight; spatiotemporal random effect denote a random intercept by country and year; and heterogeneous effect denoted a random slope as shown in (B). Due to computational burden, the results presented by (C) and (D) were on the basis of the models adjusted for all covariates except for the random slope. The 95% confidence intervals of effect estimates are shown as error bars in (A) and (C) and error ribbons in (B) and (D).

32.4–35.8% of all children <5 years of age and 30.4–35.6% of all U5Ds during 2004–2017. In 2004, within CSA, there were 51,600 U5Ds of floods (35,100 in India, 10,300 in Bangladesh, and 4,200 in Pakistan; Figure S5), accounting for 47.1% of the total; in 2017, the number of flood-associated U5Ds in CSA decreased to 18,100 (10,700 in India, 3,300 in Bangladesh, and 3,400 in Pakistan), but the proportion increased to 55.6%, suggesting a clustered pattern in the flood-associated U5Ds.

Although the abstract number of flood-associated U5Ds was reduced, the importance of protecting children from the adverse long-term effects of flood exposure should not be underestimated. The long-term impact of floods was significantly larger than the short-term impact. Combining direct deaths due to flood with those of all other natural forces together, the attributable U5Ds were less than those attributable to long-term flood exposure (Figure 4E). For instance, in 2017, all forces of nature contributed to 832 (805, 856) direct U5Ds, dramatically fewer than long-term flood exposure (i.e., 33,000 [95% CI 4000, 57,000]). In addition, flood-associated U5Ds could be prevented by interventions to improve child health. However, compared with the decreasing trend in the U5Ds caused by all types of diarrheal diseases, in some countries, such as Egypt and Indonesia, that in flood-associated U5Ds was slower (Figures 4F and S6).

In sensitivity analyses, 47.9% of children <15 years old in 2017 were exposed to flood at least once during their life course, which contributed to 2.51% of premature deaths. The spatial distributions of exposure and attributable deaths are shown in Figure S7. The temporal trends in exposure and attributable deaths among children <15 years of age are shown in Figure S8. Compared with flood-associated U5Ds, the burden of children 5–14 years of age was heavier. This may be because risks competing with flood exposure decrease with age. However, because of the limited accuracy of the input on children 5–14 years of age, that speculation needs to be evaluated.

DISCUSSION

Based on a sibling-matched case-control design, this study reports a nonnegligible burden of child mortality attributable to long-term exposure to floods in LMICs. The heterogeneity in the association between flood exposure and child mortality amplifies the between-individual differences in vulnerability to floods. About half of the flood-associated U5Ds were distributed in populous South Asian countries.

Few studies have explored the association between flood exposure and child mortality, and most have focused on short-term effects. A time-series study of 761 communities in 35 countries reported a 1.021 (95% CI 1.006–1.036) cumulative relative risk for all-cause mortality associated with exposure to floods during lag 0–60 days.[23] Nishikiori et al.[19] reported increased mortality a few days after the tsunami in Sri Lanka among the

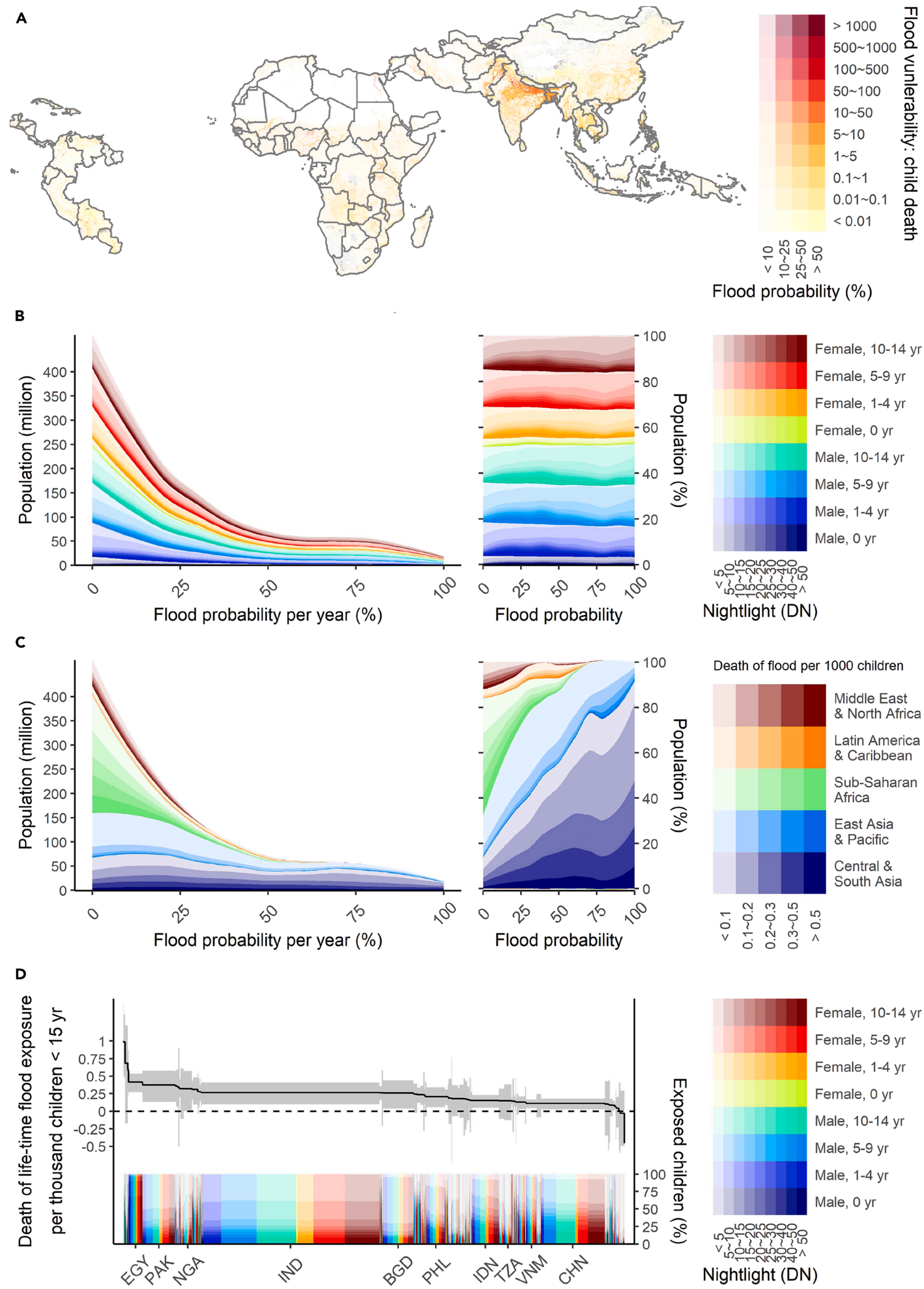

Figure 3. The distributions of flood probability and vulnerability, across the 100 low- and middle-income countries, given the 2017 population

In (A), the background colors show the gridded values of flood vulnerability, which is defined as the number of attributable deaths per 1,000 children (<15 years old); the transparence of the colors shows the probability of flood, estimated as the frequency of flooded years during 2000–2017.

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displaced population. For children <5 and 5–9 years of age, the odds ratios (ORs) were 5.90 (95% CI 4.21–8.26) and 3.94 (95% CI 2.74–5.66), respectively. Pradhan et al.[18] reported flood-mediated fatality rates of 13.3 per 1,000 girls and 9.4 per 1,000 boys. After a flood, the child mortality rate was significantly increased compared with that 1 year prior in the same village (relative risk 5.9, 95% CI 5.0–6.8). A cluster-matched cohort study in Bangladesh estimated that living in flood-prone areas was associated with an excess risk in infant mortality of 5.3 (95% CI 2.2–8.4) additional deaths per 1,000 births compared with living in non-flood-prone areas over the 30-year period between 1988 and 2017.[24] However, because long- and short-term flood exposure can affect child health by similar and different pathways, our findings are generally comparable with prior reports considering the different study population, study design, and model settings. The findings also suggested that girls were more susceptible than boys, and the young were more susceptible than the old. Previous findings are consistent with the former but not the latter (Figure 2). Various pathways have been suggested to understand the higher risk for females during and after disasters, including gender inequity, gender-based violence, and a lack of access to education.[25,26] Further studies are needed to characterize the heterogeneous effects of floods.

Previous studies have suggested multiple pathways underlying the long-term effect of flood exposure on child mortality. In the long term, exposure to floods can lead to disease and/or malnutrition if children live in an unsanitary environment contaminated by microbes, toxic chemicals, or molds.[27] In Bangladesh's deadliest flood, diarrhea was the most common cause of death, followed by respiratory tract infection.[28] Furthermore, floods influence the physical and mental health of pregnant women, leading to adverse pregnancy outcomes including preterm birth and low birthweight. Among 571 pregnant women recruited from 10 flood-relief camps, Baloch et al.[29] found 237 cases (41.50%) of low birthweight and 120 early neonatal deaths (21.01%). After the 1997 Red River flood in North Dakota, pregnant women had high levels of prenatal stress, and the relevant clinical risks were increased by 5.1%–7.1%. There were also significant increases in the risks of low birthweight (OR = 1.11; 95% CI 1.03–1.21) and preterm birth (OR = 1.09; 95% CI 1.03–1.16).[15]

Interactions between climate change and imperfect land management are key drivers of floods. Land management (such as urbanization) is related to socioeconomic development and geographic differences therein, which lead to an unequal distribution of health effects of flood exposures. For instance, in 2015, nearly 62.7% of global disasters occurred in the Asian region. Floods accounted for 41.27% of these natural disasters and was the most common type in Asia from 2000 to 2016.[30] Given the unequal distribution in exposure levels, geographically varying vulnerabilities can amplify or attenuate the risks brought by floods. Based on our findings, children in South Asia are moderately vulnerable to floods at present. Because of the co-incidence of frequent floods, populous residences, and a high proportion of vulnerable individuals, South Asia is a hotspot of flood-associated child mortality. Therefore, regional-level measures are needed to reduce the long-term health effects of floods.

In LMICs, where resources to improve land management are limited, the ability to adapt to extreme weather events, including floods, is restricted.[31] Understanding the heterogeneity in the association between flood and a health outcome is of public health importance for policymaking against natural disasters. For instance, there was a nonsignificant effect of flood exposure among well-educated mothers and the richest families, consistent with a report of a negative association between child mortality and maternal education level.[32] Considering the sex inequity and subsequent insufficient education among women in LMICs, educating women on how to cope with health risks after natural disasters could reduce the effect of flood exposure on child health. We found a close relationship between flood vulnerability and nightlight, suggesting that urbanization is key to modulating human resilience. Urban planning optimization, and improvement in environmental management, such as introducing a timely flood-warning system, would reduce vulnerability to flood exposure.

This study had several limitations. First, although we matched the samples by mother and adjusted for multiple covariates, potential confounders were missing and not controlled for, including perinatal factors, basic health conditions of children, and nutrition of children. Additionally, due to the unavailability of household mobility data and information on temporal changes in certain household socioeconomic status variables in the DHS surveys, these factors were not accounted for in our models. Second, the outcomes were self-reported, which makes recall bias inevitable. The misclassification of outcomes would bias the estimation. Third, the DHS dataset does not have information on the cause of child mortality, possibly leading to misclassification of outcomes. Fourth, there might be selection bias in the sibling-matched case-control study design. The analyzed children were less representative of one-child families, who are prevalent in cities.[33] However, the deceased children without siblings only account for 0.5% in our study, and the selection bias could have limited influence on our estimates. Additionally, in DHS, the children aged 6–15 years might not be fully accounted for, affecting the representation of this age group compared with children younger than 5 years old. Therefore, we presented the detailed results separately for children younger than 5 years old and the health impact assessment specifically focused on children younger than 5 years in 100 LMICs from 2004 to 2017. We conducted a sensitivity analysis to assess the burden of mortality among children younger than 15 years old. Fifth, for the assessment of child vulnerability to flood, only sociodemographic characteristics were considered in this study, other geographical determinants of vulnerability were overlooked due to a lack of data availability. Additionally, we utilized nightlight data to approximate a high-resolution map of socioeconomic status

(B and C) The population distributions of flood probability presented in the map (A). (B) The distribution by population characteristics and nightlight levels, the factors to explain the heterogeneity embedded in the association between flood and child mortality. (C) The distribution by regions and different levels of vulnerability.

(D) The different levels of flood vulnerability by countries, given the real-world exposure in 2017; along the x axis, width of the interval for a specific country is proportional to the number of children exposed to flood during their whole life in 2017; and the top 10 populous countries are presented by the corresponding ISO-3 codes. The 95% confidence intervals of effect estimates are shown as grey ribbons.

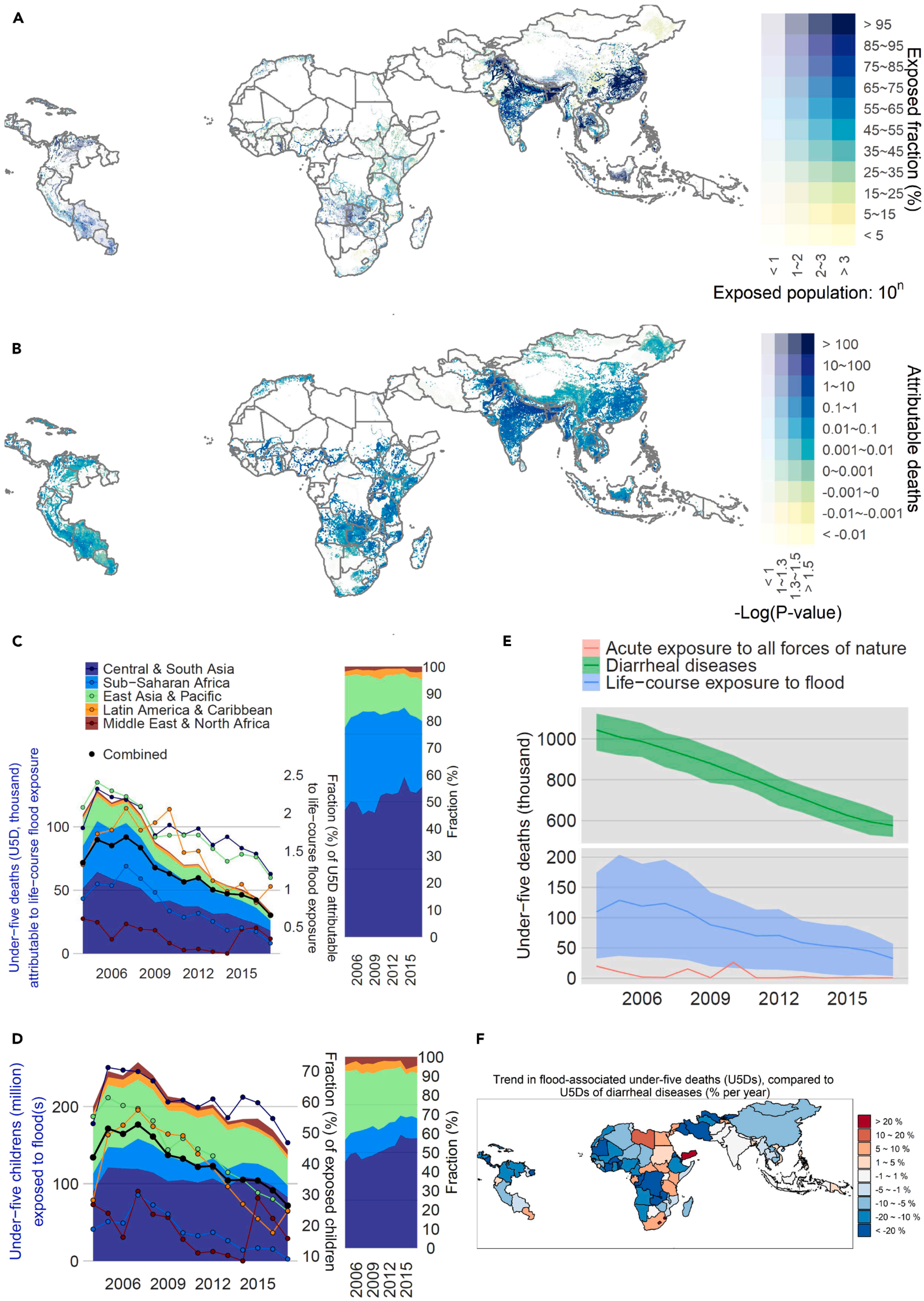

Figure 4. Spatiotemporal distributions for the under-5 deaths (U5Ds) attributable to life-course flood exposure, during 2004–2017, in the study domain of 100 low- and middle-income countries

(A and B) The spatial distributions of flood exposure and attributable U5Ds in 2010, respectively. For (B), the transparence of colors shows *p* values for effect estimates.

(legend continued on next page)

across the 100 LMICs with weak statistics, which might incorporate inherent limitations. For instance, there were more uncertainties in the nightlight-based socioeconomic estimates due to challenges in disaggregating between various economic activities, as well as the confounding effects of weather and seasonal variability. Besides, although previous studies suggested that nightlight served as a good proxy of economic activity in both urban and rural areas, the correlation between nightlight and economic indicators is higher for urban than rural areas,[34] which might lead to bias to our estimates. Sixth, we used a binary exposure variable measured by the presence of at least one flood exposure during the life course. In areas where flooding is recurrent and prevalent, the flood-attributable child mortality rate may be underestimated. Conversely, in regions where individuals experienced a single flood event over their lifetime, the attributable risk may be overestimated. Additionally, the assessment of flood exposure across 100 LMICs over a long period is challenging, and no current method yields perfect results. In our study, potential exposure misclassification may arise due to the limitations of the Global Flood Database (GFD) in accurately detecting smaller-scale floods (below 250-m resolution) or rapid flash floods. The GFD may also underrepresent the maximum flood extent, particularly in regions with complex climatic conditions (e.g., persistent cloud cover) or challenging terrain (e.g., dense forests, urban areas). Limited by the accuracy of satellite measurements of floods, exposure was coded as a dichotomous variable, hampering characterization of the intensity of flood exposure. Further studies are needed to explore how flood intensity and duration affect child health. Finally, we acknowledge that the estimated associations between flood exposure and child mortality from the 55 LMICs included in our study may not fully represent the broader context of all 100 LMICs. As a result, the findings from the vulnerability analysis for the 100 LMICs should be interpreted with caution. Further epidemiological evidence based on more representative populations from a wider range of LMICs, as well as studies employing more robust designs, is needed to strengthen these conclusions.

Conclusions

This sibling-matched case-control study combined multi-country health survey data with the state-of-the-art estimates on flood exposure, population, and baseline mortality rate to map the heterogeneous risks brought by flood exposure in LMICs. We found that flood exposure had a long-term effect on child mortality. Based on a globally representative assessment of 100 LMICs, we estimated that life-course exposure to floods was associated with 33,000 (4,000, 57,000) premature deaths of children <5 years of age in 2017. Due to frequent floods and a vulnerable population, South Asia is a hotspot of flood-associated child mortality. Regional policies to reduce vulnerability to floods are needed to improve child health in LMICs. Our study adds value by identifying the communities vulnerable to flood for the first time and providing a scientific database to plan relevant climate-health services (e.g., early warning for flood exposure).

METHODS

Study design and population

Individual records of mothers and their children (<18 years of age) were extracted from DHSs in 55 LMICs from 2000 to 2018. DHSs are nationally representative household surveys in more than 90 developing countries conducted by the US Agency for International Development, with the objective of improving the collection, analysis, and dissemination of population, health, and nutrition data for policymaking. Using a stratified two-stage cluster design, standard DHS surveys are conducted every 5 years. Trained fieldworkers conduct the surveys using uniformly designed questionnaires to collect information on socioeconomic status, fertility, reproductive history, and infant mortality. In recent DHS phases, the geographical locations of the surveyed clusters were recorded using global positioning system (GPS) devices, which allowed us to match the environmental exposure data. More detail on the public surveys is available on the official DHS website (https://www.dhsprogram.com/) or in our earlier works.[35,36]

This sibling-matched case-control study explored the association between flood exposure and child mortality at <18 years of age (simplified as child mortality below). The sibling-matched method matched the cases (child deaths) and controls (remaining live siblings) by mother, and thus minimized the confounding effects of genetic factors, family socioeconomic status, and other unmeasured familial and parental factors on child mortality and yielded robust estimates of the association between flood exposure and child mortality. In the sibling-matched case-control design, the association is mainly inferred from the coherence between temporal changes in environmental exposure and health risk changes within the same household, which is comparable to the statistical inference in a longitudinal study. Details of the sibling-matched case-control design are available in previous works.[35,37] We compared siblings born from the same mother (15–49 years of age) with at least one deceased child (case) and at least one alive child (control). Valid controls had to live equal to or longer than cases. For multiple controls, weights calculated as the case-to-control ratios were introduced into regression models, which was equivalent to creating a syngeneic control as an average of all controls matched to a specific case. Only livebirths were considered in this study. Respondents were excluded if they lacked valid GPS coordinates, a valid birth date of the child, or a valid date of death (for cases only). Ultimately, 168,762 pairs of siblings were included in the analysis. Procedures and questionnaires for DHS surveys were reviewed and

(C and D) Temporal trends in the attributable U5Ds and the relevant flood exposures from 2004 to 2017, respectively.

(E) A comparative assessment of our estimates on flood-associated U5Ds with those on U5Ds of all natural forces (including hurricane, earthquake, tsunami, tornado, lightning strike, volcanic eruption, avalanche, and flood) and of diarrheal diseases (a potential pathway to explain the linkage between long-term flood exposure and child mortality), which were obtained from the Global Burden of Diseases study 2019 (https://vizhub.healthdata.org/gbd-results/, accessed April 8, 2023). The 95% confidence intervals of effect estimates are showns as error ribbons.

(F) Country-level trend in flood-associated U5Ds from 2004 to 2017, compared with the U5Ds caused by diarrheal diseases. The trend was estimated by Sen's slopes, and a positive slope showed that the speed of reduction in flood-associated U5Ds was slower than that in diarrheal diseases.

approved by the ICF Institutional Review Board, and so consent was not required for use of the data.

Exposure assessment

Flood exposure data were obtained from the Global Flood Database.[38] This database systematically maps the maximum observed surface-water extent during 913 large flood events documented by the Dartmouth Flood Observatory (DFO) from 2000 to 2018 based on Earth-observing satellites. In total, 12,179 images of 250-m spatial resolution obtained by the moderate-resolution imaging spectroradiometer (MODIS) on NASA's Terra and Aqua satellites, were analyzed to produce 913 flood maps, which covered 2.23 million km^2. Most of the flood events occurred in Asia ($n = 398$), followed by the Americas ($n = 223$) and Africa ($n = 143$). This method was validated using *in situ* observational data with a 30-m spatial resolution from Landsat for 30,685 points and yielded a mean accuracy of 83% for flood exposure.[38]

We collected measurements of fine particulate matter ($PM_{2.5}$) and nightlight data at a spatial resolution of $0.01^\circ \times 0.01^\circ$ (about 1×1 km) for the 55 LMICs during 2000–2018 from multiple sources. The monthly concentrations of ground surface $PM_{2.5}$ were measured by combining satellite retrievals of aerosol optical depth, chemical transport modeling, and ground-based measurements.[39] Annual nightlight data were measured using the visible and infrared sensors of multiple satellites, and were harmonized as reported previously.[40] The nightlight value was considered a proxy for the urbanicity and socioeconomic status of a participant's neighborhood.

The primary time window for environmental exposures, including flood, $PM_{2.5}$, and nightlight, was selected as the whole life course (also known as long-term exposure). To capture all pathways affecting child health, maternal exposure was included, and thus the life course was defined from 9 months preceding the birthdate to the month of mortality. Flood exposure was coded as a binary exposure variable according to the presence of satellite flood areas within a 10-km buffer surrounding the centroid of living cluster, i.e., the survey cluster in DHSs. $PM_{2.5}$ and nightlight were continuous variables calculated as the average exposure over the lifetime. For sensitivity analysis, we set two secondary time windows for flood exposure. The short-term time window was the month of death, and the medium-term was the 10 months preceding death. Because the effects of flood might vary according to developmental stage at exposure (e.g., maternal vs. childhood exposure), we matched the time window for each case-control pair. Therefore, for a control, the exposure time window was ended at the age (months) of death of the corresponding case. We re-ran the models using other buffers (5–15 km) to define flood exposure.

Statistical analysis

The primary health outcome was a child's survival status as a binary variable. In this matched case-control study, a conditional logit regression model was used to test the association between flood exposure and child mortality:

$$\mathrm{Logit}(y_{i,j}) = x_{i,j}\beta + \eta_k(u_{i,j})x_{i,j} + \boldsymbol{z}_{i,j}\boldsymbol{\gamma} + \theta_i \ldots\ldots \quad \text{(Equation 1)}$$

where i and j are indexes for a mother and her children, respectively; y is the child's survival status (live or dead); x is flood exposure; $\boldsymbol{z}$ is adjusted covariates; θ_i is fixed effects by mothers; and $\eta()$ is a varying-efficient function of nightlight (u) by sex-age group (k), and β and $\boldsymbol{\gamma}$ are regression coefficients. The fixed effects (θ_i) enable adjustment for time-independent household and maternal confounders, such as genetic factors and household socioeconomic status. $\eta()$ was parameterized using spline basis functions of nightlight with sex-age-specific coefficients. To set $\eta()$ as a random slope, the corresponding regression coefficients were penalized by L_2-regularization. The adjusted covariates were child sex, multiple births (no or yes), splines of birth order (5 degrees of freedom [df]), splines of temporal index (4 df per year), $PM_{2.5}$ concentration, nightlight, and a random intercept by spatiotemporal index as country-year. We calculated the robust standard error in the conditional logit regression model to address autocorrelation within samples. The overall association between flood exposure and child mortality was evaluated according to odds ratios (ORs = $\exp[\beta]$) with 95% CIs. The subgroup-specific OR, given a combination of sex, age, and nightlight level, was further quantified as $\exp[\beta + \eta_k(u_{i,j})]$.

Health impact assessments

Consistent with previous health impact assessments,[37,41] we generalized the estimated risk to other LMICs, and thus the subgroup-specific association between flood exposure and child mortality, given a combination of sex, age, and nightlight level, from a sample of 55 LMICs is extrapolated to 100 LMICs for the health impact assessments. To evaluate the burden of child mortality caused by floods, we conducted a risk assessment by calculating 5×5-km grid of attributable number and fraction based on life-course exposure using the following equation[41]:

$$AF_{s,y,k} = 1\text{–}1 \;/\exp\left[\beta + \eta_k(u_{s,y})\right] \ldots\ldots \quad \text{(Equation 2)}$$

$$AN_{s,y} = \Sigma_k\, P_{s,y,k} * B_{s,y,k} * AF_{s,y,k},\, AN_{c,y} = \Sigma_{s\in c}\, AN_{s,y} \ldots\ldots \quad \text{(Equation 3)}$$

$$PAF_{s,y} = AN_{s,y}/\Sigma_k\, Pop_{s,y,k},\, PAF_{c,y} = AN_{c,y}/\Sigma_{s\in c}\,\Sigma_k\, Pop_{s,y,k} \ldots\ldots \quad \text{(Equation 4)}$$

$$EF_{s,y} = \Sigma_k\, P_{s,y,k}/\Sigma_k\, Pop_{s,y,k} \ldots\ldots \quad \text{(Equation 5)}$$

where s, y, and k are indexes for grid, year, and sex-age group of assessment, respectively; c is the country index, Pop and P are the numbers of all children and children exposed, respectively; B is the baseline mortality rate, AN and AF are the attributable number and fraction, PAF is the population attributable fraction, and EF is the fraction of children exposed during the life course. Population maps with a spatial resolution of 1 km for 2000 to 2017 were obtained from the Gridded Population of the World (WorldPop, version 4), and aggregated into 5×5-km grid to reduce the computational burden. Within a WorldPop pixel, the fraction of children exposed was determined as the area covered by flooded pixels (i.e., the DFO pixels with a 10-km buffer). The baseline mortality rates were from an ensemble of small-area estimates (5-km grid or county-level unit) of U5Ds from 2000 to 2017, produced by the Global Burden of Diseases (GBD) study. Limited by availability of high-resolution mortality data, our assessment focused on children <5 years of age in 100 LMICs from 2004 to 2017. We also assessed the burden among children <15 years of age as a sensitivity analysis, in which the gridded morality rates for children 5–9 and 10–14 years of age were estimated by multiplying the U5D rate in the same grid by the country-level calibration ratio, obtained from the GBD life tables. To account for life-course exposure for children 14 years of age, the temporal coverage for the secondary assessment was restricted to 2014 to 2017.

We evaluated vulnerability ($V_{s,y}$) to flood by jointly considering the heterogeneous effect of exposure and non-optimal baseline of health, as follows:

$$\begin{aligned} V_{s,y} &= AN_{s,y} \Big/ \Sigma_k P_{s,y,k} \\ &= \Sigma_k w_{s,y,k} * B_{s,y,k} * \left\{1\text{–}1 \Big/ \exp\left[\beta + \eta_k\left(u_{s,y}\right)\right]\right\}, w_{s,y,k} \\ &= P_{s,y,k} \Big/ \Sigma_k P_{s,y,k}\ldots\ldots \end{aligned} \quad \text{(Equation 6)}$$

The vulnerability index ($V_{s,y}$) is a weighted-average product of subgroup-specific effect and baseline mortality rate, and the weights are fractions of children exposed. The index can be calculated for a real-world flood exposure scenario, or a counterfactual scenario in which all children were exposed. The risk for flooding is co-determined by flood vulnerability and probability. For each pixel, we defined a flooded year as a flood occurring at least once during a 12-month period and calculated the frequency of flood years from 2000 to 2017 as the probability of flood exposure, which was presented jointly with vulnerability for a generalizable interpretation of the effect of flood on child mortality.

The flowchart of study design and statistical analyses is shown in Figure S1. Statistical analyses were conducted using R (version 4.1.3; The R Foundation for Statistical Computing, Vienna, Austria).

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Dr. Tao Xue (txue@hsc.pku.edu.cn).

Materials availability

This study did not generate new unique materials.

Data and code availability

The datasets used in this study are publicly available. The Demographic and Health Survey (DHS) dataset, Global Flood Database (GFD), $PM_{2.5}$ dataset, nightlight dataset, population datasets of children, and child mortality dataset are available from https://www.dhsprogram.com/, https://global-flood-database.cloudtostreet.ai/, https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.02, https://doi.org/10.6084/m9.figshare.9828827.v2, https://www.worldpop.org/, and https://ghdx.healthdata.org/gbd-2019. The code used for the main analysis and any additional information required for reanalyzing the data reported in this paper are available from the lead contact upon reasonable request.

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AUTHOR CONTRIBUTIONS

P.L.: Conceptualization, formal analysis, writing – original draft, writing – review & editing, visualization. M.T.: Formal analysis, writing – original draft, writing – review & editing, visualization. J.W.: Validation, writing – review & editing. X.M.: Investigation, data curation. X.F.: Investigation, data curation. X.S.: Data curation. J.L.: Writing – review & editing, supervision. T.X.: Conceptualization, Formal analysis, writing – original draft, writing – review & editing, supervision, funding acquisition. All authors have directly accessed and verified the underlying data reported in the manuscript. All authors confirm that they have full access to all the data in the study and accept responsibility to submit for publication.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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