Supplementary Materials

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1. Methods

1.1 Mortality data

The MCC Network collected and updated daily time-series data on death counts from relevant authorities of multiple countries/territories globally. The details had been provided in previous publications [1,2]. The most updated MCC database had all-cause mortality data (if not available, represented by non-external causes [ICD-9th Revision codes 0–799 or ICD-10 codes A0–R99] mortality) of 792 communities from 44 countries/territories; cardiovascular mortality data of 631 communities from 29 countries/territories; respiratory mortality data of 639 communities from 28 countries/territories. The COD URF registered the date, cause, and Statistical Area Level 3 (SA3) for residence of all death in Australia, which was aggregated as daily death counts of SA3s. Since some SA3s were sparsely populated, only SA3s in metropolitan areas (e.g., the Great Sydney) were considered. Consequently, mortality data from 171 (out of 345) SA3s in seven states (i.e., New South Wales, Victoria, Queensland, South Australia, Western Australia, Tasmania, and Northern Territory) during 2006-2017 were included, and the mortality data of the three cities of Australia from the MCC database were excluded because of duplications. The New Zealand integrated data infrastructure (IDI) provided the date, cause, and territorial authority (TA) for residence of all death in New Zealand. All deaths during 2001-2018 in all (N=67) TAs of New Zealand were included. The International Network for the Demographic Evaluation of Populations and their Health (INDEPTH) Network database provides all-cause mortality counts data in 2000-2016, which were retrieved from 32 health and demographic surveillance systems (HDSS) sites in Africa and Asia that were not overlapped with the MCC database. The health data were representative of the whole population in each HDSS site, and more information had been presented by previous publications [3,4]. The COD URF, IDI, and INDEPTH datasets were collected because the MCC database only covered 52 locations in one country in Sub-Saharan Africa and three cities (i.e., Sydney, Melbourne, and Brisbane) in Australia and New Zealand.

1.2 Demographic, socioeconomic status, and population health variables

Demographic data of 2010 were obtained from the Gridded Population of the World (GPW, version 4) dataset from the Socioeconomic Data And Applications Center (SEDAC), which were estimates of population counts in a spatial resolution of 1km and were consistent with national censuses and population registers [5]. Based on the gridded population data and community boundaries, numbers of older population (i.e., aged 65 years and older) and total population in 2010 were estimated for each community. For each community, proportion of older population was calculated by dividing the number of older population by the total population, and the population density was defined as number of population per square kilometer.

Global data of human development index (HDI) attempted to quantify human well-being on a subnational level (e.g., states and provinces) through a combination of three dimensions: education, health and standard of living [6]. HDI data in 2010 were obtained from the Global Data Lab. The index ranged from 1 to 100, and a higher HDI indicates a higher level of well-being. The HDI of each community was defined as the HDI of the subnational area where the community located.

Infant mortality rate (IMR) had been regarded as an indicator of population health status [7]. Global estimates of subnational IMR were obtained from the SEDAC. Considering only estimates of 2000 and 2015 were available, and the study periods were generally 2000-2019 across communities, we chose the estimates of 2015. IMR were stored in a gridded format with a spatial resolution of 1km. The IMR for each community in 2015 was estimated by using the gridded IMR data and the gridded population counts data in 2015, which was also obtained from the SEDAC [5].

1.3 Community-specific model

Community-specific flood-mortality associations were examined using a time-series Poisson regression as shown:

$$\log(D_{ij}) = cb(Flood_{ij}) + bs(t_j) + bs(doy_j) + dow_j \; + \; cb(Temp_{ij})$$

Where D_{ij} is the death count in community i on day j; $Flood_{ij}$ is the binary flood exposure indicator, of which the lag-response association is modeled using a natural cubic B spline with three degrees of freedom through a crossbasis function (three degrees of freedom were selected to allow for a nonlinear association while maximizing the statistical power); t_j is a cubic B spline with three degrees of freedom for the date on day j to model long term trends; doy_j is a cyclic cubic B spline with three equally spaced knots for day of the year on day j; dow_j is a categorical variable for day of week on day j; and $Temp_{ij}$ is a crossbasis function of daily mean temperature over 0-21 lag days in community i on day j, of which the exposure-response association is modeled with a quadratic B spline with three internal knots placed at the 10^{th}, 75^{th}, and 90^{th} percentiles, and the lag-response association is modeled using a natural cubic B spline with an intercept and three internal knots placed at equally spaced values in the log scale [1].

1.4 Sensitivity analyses

We undertook sensitivity analyses to examine the robustness of our results. Namely, assuming different maximum lag periods (30, 40, 50, 90, or 120 days) for the impact of floods on mortality; modeling the lag-response associations of flood exposure using a natural cubic B spline with different degrees of freedom (DF = 2 or 4); modeling the exposure-response association of temperature with different a spline (i.e., natural cubic B spline), places of knots (i.e., equally spaced), and numbers of knots (i.e., 2 and 4 equally spaced knots); and modeling the lag-response association of temperature with different a spline (i.e., cubic B spline), numbers of knots (i.e., 2 and 4 internal knots placed at equally spaced values in the log scale), and maximum lag periods (i.e., 14 and 28 days). The effect estimates from the sensitivity analysis models were compared with the effect estimates produced by our primary models, using fixed effect meta-regressions with no statistical adjustment [8].

1.5 Calculation of attributable fraction

First, the number of annual deaths attributable to flood exposure was calculated for each community using the country/territory-level lag-response estimates [9]. Then, the total number of annual attributable deaths was divided by the total number of annual deaths to derive the attributable fraction (AF) for each country/territory. The calculation (of country/territory-specific AFs) was performed using the following formulas:

$$b\_AF_j = 1 - \exp(-\sum_{l=0}^{L} \beta_{j-l})$$

$$AN_j = n_j * \ b\_AF_j$$

$$AF = \frac{\sum {AN_i}/{d_i}}{\sum {n_i}/{d_i}}$$

Where: b_AF_j is the attributable fraction of mortality due to the flood exposure on day j, with backward approach; j is the day when deaths occur; l is the lag time; L is the maximum lag time; β_{j-l} is the effect estimates associated with flood exposure on day $j-l$; AN_j is the number of deaths attributable to flood exposure on day j; n_j is the registered number of deaths on day j; AN_i is the attributable deaths to flood exposure in community i during the study period; n_i is the deaths in community i during the study period; d_i is the study period (years) of community i; $\sum {AN_i}/{d_i}$ is the total number of annual attributable deaths in the country/territory; $\sum {n_i}/{d_i}$ is the total number of annual deaths [9].

2. Results

Table S1. Descriptive statistics of the 761 communities by country/territory

	Income class[a]	Number of communities	Study period	Number of flood events[b]	Flooded days per year[c]	All cause deaths[d]	Cardiovascular deaths	Respiratory deaths
Northern America								
Canada	H	10	2000-2015	14	0.9 (0.5)	750583	236419	64576
USA	H	148	2000-2006	70	3.8 (4.7)	5911528	1796072	582445
Latin America and the Caribbean								
Argentina	UM	3	2005-2015	4	1.6 (1.9)	686333	NA	NA
Brazil	UM	21	2000-2018	51	4.2 (4.8)	3819621	1026449	394535
Chile	UM	4	2004-2014	2	1.3 (0.5)	325462	NA	NA
Colombia	UM	5	2000-2013	16	12.4 (0.9)	843633	237346	88819
Mexico	UM	6	2000-2014	9	1.8 (2.1)	1920315	643690	236568
Peru	UM	16	2008-2014	11	11.2 (15.3)	604595	NA	NA
Eastern Asia								
Japan	H	43	2000-2015	18	1.0 (0.7)	7170326	2047878	1080097
Mainland China	UM	10	2001-2015	21	16.7 (16.0)	731525	304313	100880
South Korea	H	34	2000-2018	23	1.1 (1.0)	2647364	602332	199368
Taiwan	UM	3	2001-2014	14	3.4 (1.2)	907141	199305	93464
South East Asia								
Philippines	LM	12	2006-2019	19	7.6 (1.1)	796933	288555	116027
Thailand	UM	62	2000-2008	40	36.5 (28.8)	1666292	299721	205900
Australia and New Zealand								
Australia	H	94	2009-2017	15	3.4 (7.4)	401584	119454	36007
New Zealand	H	55	2000-2018	32	0.7 (0.8)	523282	183559	45343
Eastern Europe								
Czech Republic	H	4	2000-2015	10	5.7 (0.7)	505932	246331	29860
Moldova	LM	2	2003-2010	3	2.4 (0.0)	2262	NA	NA
Romania	UM	8	2000-2016	23	4.8 (2.6)	697505	NA	NA
Northern Europe								
Ireland	H	1	2000-2007	1	1.7 (0.0)	80436	21288	11905
UK	H	66	2000-2016	22	6.6 (4.6)	3542588	1149607	514056
Southern Europe								
Italy	H	10	2006-2015	7	1.2 (0.8)	579943	NA	NA
Portugal	H	6	2000-2018	2	1.0 (0.0)	967490	303179	107939
Spain	H	45	2000-2014	21	0.9 (0.7)	1529149	496468	184407
Western Europe								
France	H	19	2000-2015	17	0.5 (0.4)	1734312	NA	106092
Germany	H	10	2000-2015	11	0.8 (2.9)	1819821	NA	NA
Netherland	H	5	2000-2016	2	0.5 (0.2)	338448	NA	NA
Switzerland	H	7	2000-2013	7	1.1 (1.5)	154576	56968	9731
Sub-Saharan Africa								
Burkina Faso	L	3	2000-2015	6	5.8 (6.4)	16248	NA	NA
Ethiopia	L	1	2006-2015	2	12.7 (0.0)	3929	NA	NA
Ghana	LM	3	2000-2014	9	13.5 (8.0)	26586	NA	NA
Kenya	L	2	2003-2015	9	13.0 (10.3)	10859	NA	NA
Senegal	LM	3	2000-2016	4	6.1 (0.8)	9245	NA	NA

South Africa	UM	38	2000-2016	27	3.0 (3.8)	5840325	855882	680276
Tanzania	L	2	2000-2014	9	13.0 (7.0)	15304	NA	NA

[a]Income class: low (L), lower-middle (LM), upper-middle (UM), high (H).
[b]Number of flood events that impacted the included communities during the study period.
[c]Median (IQR) of flood days per year across the included communities during the study period.
[d]All cause mortality data were not available, and only non-external mortality data were collected for the 142 communities from Spain (N = 45), Thailand (62), Mainland China (10), Brazil (21), Argentina (3), and Ireland (1). Abbreviations: IQR = interquartile range; USA = the United States of America; UK = the United Kingdom.

Table S2. I^2 statistics and results of Cochran's Q tests of meta-analyses

Variable	All cause mortality		Cardiovascular mortality		Respiratory mortality	
	I^2	*p*-value	I^2	*p*-value	I^2	*p*-value
Global	45%	<.001	23%	<.001	36%	<.001
Northern America	32%	<.001	9%	0.078	33%	<.001
Canada	50%	0.001	34%	0.041	34%	0.044
USA	30%	<.001	5%	0.2	32%	<.001
Latin America and the Caribbean	46%	<.001	46%	<.001	59%	<.001
Argentina	33%	0.176	NA	NA	NA	NA
Brazil	20%	0.094	43%	0.001	25%	0.07
Chile	0%	0.955	NA	NA	NA	NA
Colombia	80%	<.001	51%	0.019	61%	0.002
Mexico	0%	0.934	24%	0.222	51%	0.032
Peru	38%	0.007	NA	NA	NA	NA
Eastern Asia	40%	<.001	28%	<.001	40%	<.001
Japan	14%	0.095	22%	0.016	33%	<.001
Mainland China	78%	<.001	70%	<.001	72%	<.001
South Korea	25%	0.014	6%	0.31	0%	0.777
Taiwan	65%	0.01	0%	0.632	69%	0.004
South East Asia	62%	<.001	43%	<.001	42%	<.001
Philippines	34%	0.029	2%	0.432	60%	<.001
Thailand	63%	<.001	44%	<.001	25%	0.002
Australia and New Zealand	41%	<.001	13%	0.014	11%	0.032
Australia	54%	<.001	25%	<.001	4%	0.293
New Zealand	0%	0.753	0%	0.917	19%	0.026
Eastern Europe	13%	0.246	0%	0.464	36%	0.123
Czech Republic	0%	0.611	0%	0.464	36%	0.123
Moldova	0%	0.465	NA	NA	NA	NA
Romania	29%	0.101	NA	NA	NA	NA
Northern Europe	21%	0.006	19%	0.012	11%	0.106
Ireland	NA	NA	NA	NA	NA	NA
UK	21%	0.006	19%	0.013	12%	0.086
Southern Europe	37%	<.001	0%	0.626	31%	<.001
Italy	67%	<.001	NA	NA	NA	NA
Portugal	0%	0.46	5%	0.4	0%	0.72
Spain	18%	0.043	0%	0.947	24%	0.008
Western Europe	41%	<.001	3%	0.421	18%	0.114
France	36%	0.005	NA	NA	29%	0.038
Germany	55%	<.001	NA	NA	NA	NA
Netherland	40%	0.069	NA	NA	NA	NA
Switzerland	28%	0.129	3%	0.421	0%	0.912
Sub-Saharan Africa	61%	<.001	27%	0.011	43%	<.001
Burkina Faso	0%	0.992	NA	NA	NA	NA
Ethiopia	NA	NA	NA	NA	NA	NA
Ghana	0%	1	NA	NA	NA	NA
Kenya	0%	0.947	NA	NA	NA	NA

Senegal	0%	0.451	NA	NA	NA	NA
South Africa	71%	<.001	27%	0.011	43%	<.001
Tanzania	0%	0.931	NA	NA	NA	NA
Climate						
Tropical	56%	<.001	45%	<.001	43%	<.001
Arid	30%	0.006	11%	0.256	44%	0.001
Temperate	44%	<.001	15%	<.001	35%	<.001
Continental	31%	<.001	23%	0.003	27%	<.001
Polar	0%	0.425	NA	NA	NA	NA
Income						
High	36%	<.001	12%	<.001	28%	<.001
Upper-middle	64%	<.001	48%	<.001	51%	<.001
Lower-middle	8%	0.294	2%	0.432	60%	<.001
Low	0%	0.996	NA	NA	NA	NA
Human development index						
Q4: >20.1	60%	<.001	46%	<.001	55%	<.001
Q3: 5.9-20.1	37%	<.001	6%	0.174	29%	<.001
Q2: 1.0-5.9	24%	<.001	13%	0.013	36%	<.001
Q1: <1.0	44%	<.001	15%	0.005	15%	0.004
Infant mortality rates (%)						
Q1: <0.8	25%	<.001	5%	0.213	29%	<.001
Q2: 0.8-2.8	48%	<.001	20%	<.001	27%	<.001
Q3: 2.8-6.7	32%	<.001	13%	0.011	38%	<.001
Q4: >6.7	59%	<.001	43%	<.001	48%	<.001
Proportion of older population (%)						
Q1: <9	59%	<.001	36%	<.001	45%	<.001
Q2: 9-13	49%	<.001	31%	<.001	36%	<.001
Q3: 13-16	26%	<.001	11%	0.029	27%	<.001
Q4: >16	31%	<.001	6%	0.152	33%	<.001
Population density (per km^2)						
Q1: <152	39%	<.001	6%	0.171	26%	<.001
Q2: 152-526	40%	<.001	26%	<.001	11%	0.021
Q3: 526-2010	47%	<.001	19%	<.001	44%	<.001
Q4: >2010	51%	<.001	31%	<.001	53%	<.001

Note: P values were estimated through Cochran's Q tests. Abbreviations: USA = the United States of America; UK = the United Kingdom. Human development index, infant mortality rates, proportion of older population, and population density were categorized by their quartiles among the 761 community. Abbreviations: Q = quartile.

Table S3. Results of sensitivity analyses by changing maximum lag days and degrees of freedom of the lag-response associations of flood exposure

	All cause mortality		Cardiovascular mortality		Respiratory mortality	
Model	Cumulative RR	P value for difference	Cumulative RR	P value for difference	Cumulative RR	P value for difference
Primary	1.021 (1.006 to 1.036)	Ref	1.021 (0.999 to 1.043)	Ref	1.049 (1.008 to 1.092)	Ref
Maximum lag period						
30	1.017 (1.007 to 1.027)	0.652	1.024 (1.008 to 1.041)	0.788	1.049 (1.021 to 1.078)	0.978
40	1.021 (1.009 to 1.033)	0.998	1.026 (1.008 to 1.045)	0.700	1.054 (1.022 to 1.087)	0.871
50	1.023 (1.009 to 1.036)	0.861	1.026 (1.005 to 1.047)	0.737	1.061 (1.024 to 1.100)	0.696
90	1.024 (1.004 to 1.044)	0.797	1.018 (0.993 to 1.044)	0.896	1.038 (0.990 to 1.088)	0.713
120	1.028 (1.004 to 1.052)	0.616	1.007 (0.979 to 1.036)	0.471	1.049 (0.993 to 1.108)	0.980
Degrees of freedom						
2	1.020 (1.006 to 1.035)	0.967	1.018 (0.997 to 1.040)	0.878	1.041 (1.002 to 1.082)	0.776
4	1.022 (1.007 to 1.037)	0.910	1.025 (1.003 to 1.047)	0.792	1.062 (1.021 to 1.106)	0.671

Note: P values for difference were estimated by fixed effect meta-regression with no statistical adjustment because these models were based on the same population. In the primary model, the maximum lag period was 60 days, and the degrees of freedom of lag-response association was 3.

Table S4. Results of sensitivity analyses by changing the lag-exposure-response associations of temperature

Model	All cause mortality		Cardiovascular mortality		Respiratory mortality	
	Cumulative RR	P value for difference	Cumulative RR	P value for difference	Cumulative RR	P value for difference
Primary	1.021 (1.006 to 1.036)	Ref	1.021 (0.999 to 1.043)	Ref	1.049 (1.008 to 1.092)	Ref
Exposure-response association						
Natural cubic B-spline	1.020 (1.005 to 1.035)	0.914	1.020 (0.998 to 1.042)	0.961	1.047 (1.007 to 1.089)	0.942
Equally spaced 3 knots	1.021 (1.006 to 1.036)	1.000	1.021 (0.999 to 1.044)	0.965	1.047 (1.007 to 1.089)	0.941
Equally spaced 2 knots	1.020 (1.005 to 1.035)	0.916	1.021 (0.999 to 1.043)	0.988	1.047 (1.007 to 1.090)	0.941
Equally spaced 4 knots	1.020 (1.005 to 1.035)	0.959	1.022 (1.000 to 1.045)	0.934	1.046 (1.005 to 1.088)	0.902
Lag-response association						
Cubic b-spline	1.021 (1.006 to 1.036)	0.993	1.021 (0.999 to 1.043)	0.990	1.049 (1.009 to 1.092)	0.998
Number of knots is 2	1.021 (1.006 to 1.036)	0.988	1.021 (0.999 to 1.043)	0.999	1.049 (1.008 to 1.091)	0.984
Number of knots is 4	1.021 (1.006 to 1.036)	0.998	1.021 (0.999 to 1.043)	0.998	1.050 (1.009 to 1.092)	0.995
Maximum lag period is 14 days	1.021 (1.006 to 1.036)	0.997	1.021 (0.999 to 1.043)	0.998	1.050 (1.009 to 1.092)	0.999
Maximum lag period is 28 days	1.021 (1.006 to 1.036)	0.998	1.021 (0.999 to 1.043)	0.999	1.049 (1.009 to 1.092)	0.999

Note: P values for difference were estimated by fixed effect meta-regression with no statistical adjustment because these models were based on the same population. In the primary model, the lag-exposure-response association of temperature was modelled by using a cross basis function of daily mean temperature with a maximum lag period of 21 days, of which the exposure-response association was modelled with a quadratic B spline with three internal knots placed at the 10th, 75th, and 90th percentiles, and the lag-response association was modelled using a natural cubic B spline with an intercept and three internal knots placed at equally spaced values in the log scale.

Table S5. Annual flood-attributable deaths in communities impacted by floods, by country/territory

Variable	All cause mortality	Cardiovascular mortality	Respiratory mortality
Northern America			
Canada	23 (-10 to 55)	18 (2 to 33)	6 (-2 to 14)
USA	268 (1 to 530)	132 (44 to 219)	93 (19 to 165)
Latin America and the Caribbean			
Argentina	45 (12 to 76)	NA	NA
Brazil	104 (31 to 174)	96 (24 to 172)	70 (33 to 108)
Chile	1 (-34 to 36)	NA	NA
Colombia	-69 (-281 to 119)	14 (-28 to 54)	-28 (-84 to 20)
Mexico	126 (30 to 221)	-106 (-310 to 68)	-119 (-402 to 60)
Peru	9 (-86 to 98)	NA	NA
Eastern Asia			
Japan	78 (-61 to 217)	-2 (-68 to 63)	25 (-48 to 96)
Mainland China	416 (-114, 899)	211 (-155, 524)	136 (-93, 315)
South Korea	61 (11 to 110)	-5 (-31 to 18)	9 (-1 to 18)
Taiwan	46 (-10, 98)	4 (-12, 20)	13 (-23, 44)
South East Asia			
Philippines	-26 (-114 to 63)	27 (-12 to 65)	-56 (-111 to -7)
Thailand	-195 (-567 to 163)	-179 (-302 to -61)	-10 (-80 to 58)
Australia and New Zealand			
Australia	16 (-78 to 105)	19 (-13 to 49)	17 (5 to 27)
New Zealand	7 (-5 to 18)	4 (-3 to 10)	8 (4 to 11)
Eastern Europe			
Czech Republic	8 (-19 to 34)	-8 (-32 to 14)	11 (0 to 21)
Moldova	0 (-3 to 2)	NA	NA
Romania	20 (0 to 38)	NA	NA
Northern Europe			
Ireland	8 (-85 to 76)	5 (-23 to 23)	-3 (-21 to 10)
UK	-133 (-191 to -74)	9 (-26 to 44)	-83 (-114 to -53)
Southern Europe			
Italy	-94 (-202 to 5)	NA	NA
Portugal	-15 (-36 to 4)	-15 (-28 to -3)	13 (9 to 17)
Spain	-19 (-64 to 25)	4 (-20 to 27)	-3 (-23 to 14)
Western Europe			
France	0 (-45 to 44)	NA	3 (-5 to 11)
Germany	56 (4 to 108)	NA	NA
Netherland	-3 (-21 to 13)	NA	NA
Switzerland	-13 (-35 to 6)	-4 (-10 to 2)	-2 (-5 to 0)
Sub-Saharan Africa			
Burkina Faso	7 (-8 to 18)	NA	NA
Ethiopia	3 (-40 to 15)	NA	NA
Ghana	2 (-22 to 21)	NA	NA
Kenya	10 (0 to 19)	NA	NA
Senegal	-2 (-24 to 7)	NA	NA
South Africa	267 (-151 to 651)	9 (-16 to 34)	25 (-13 to 60)

Tanzania	5 (-6 to 13)	NA	NA

Note: The attributable numbers of death were calculated using pooled country/territory level risk estimates. Abbreviations: USA = the United States of America; UK = the United Kingdom.

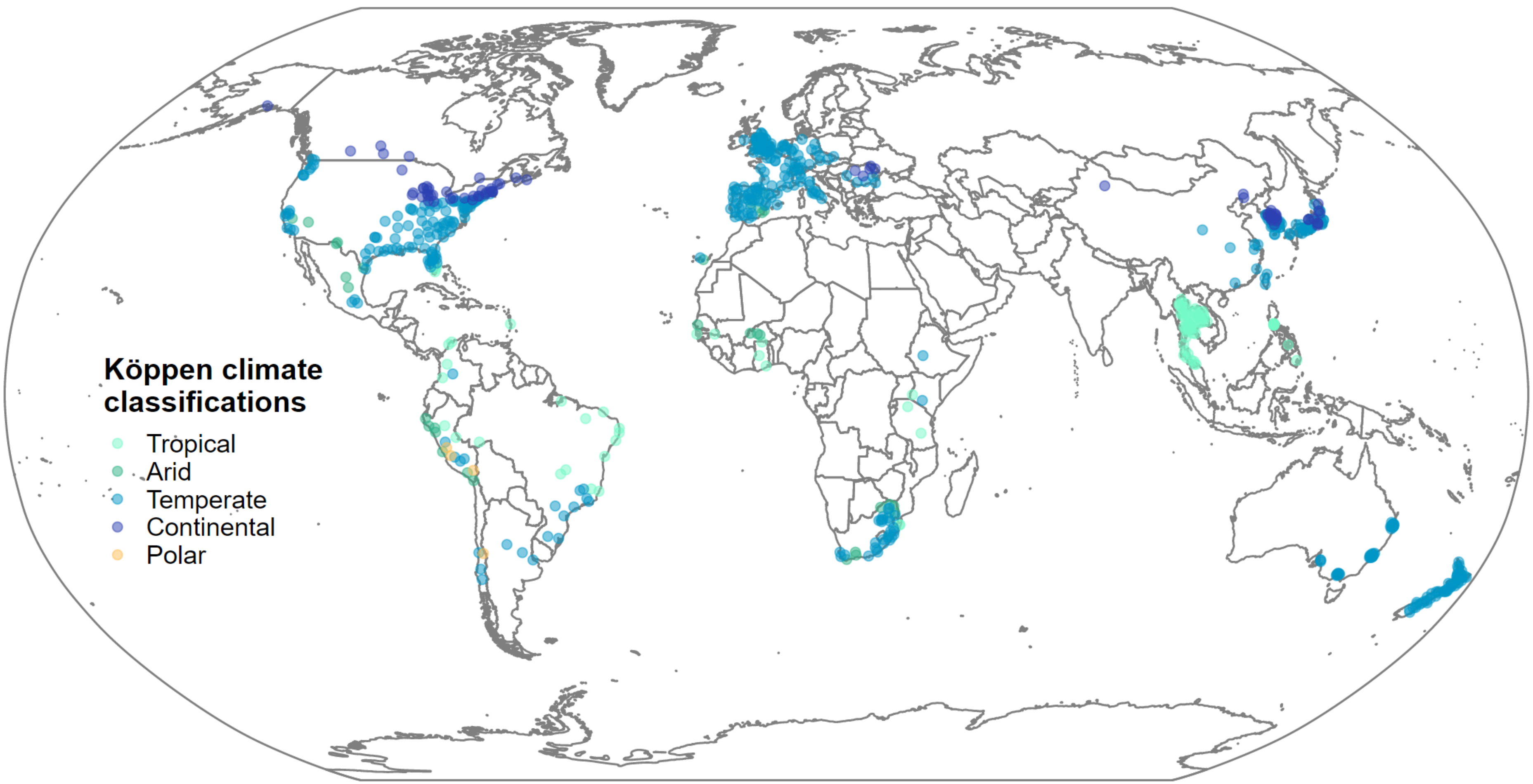

Figure S1. Köppen climate classifications in the 761 communities.

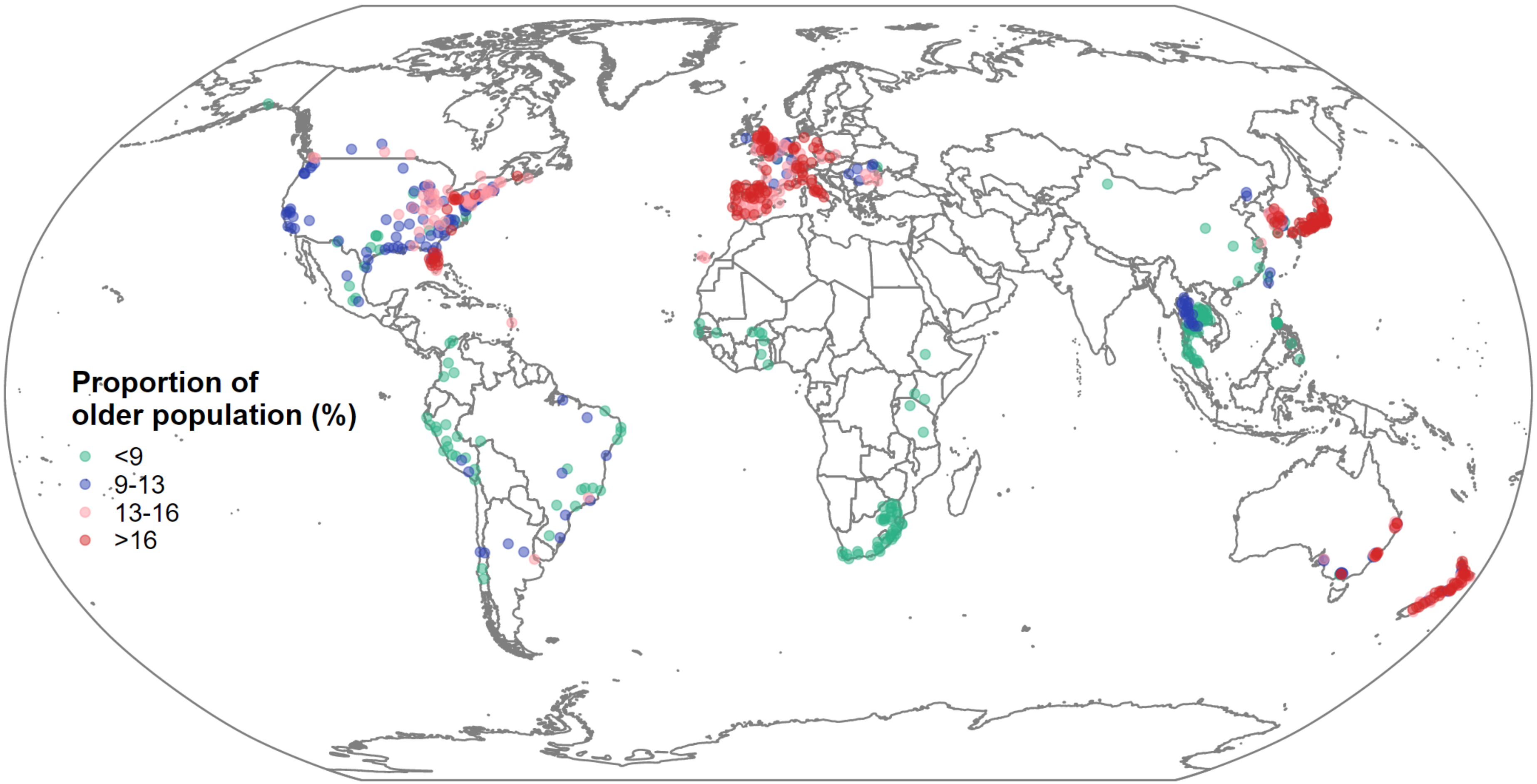

Figure S2. Proportions of older population in the 761 communities.

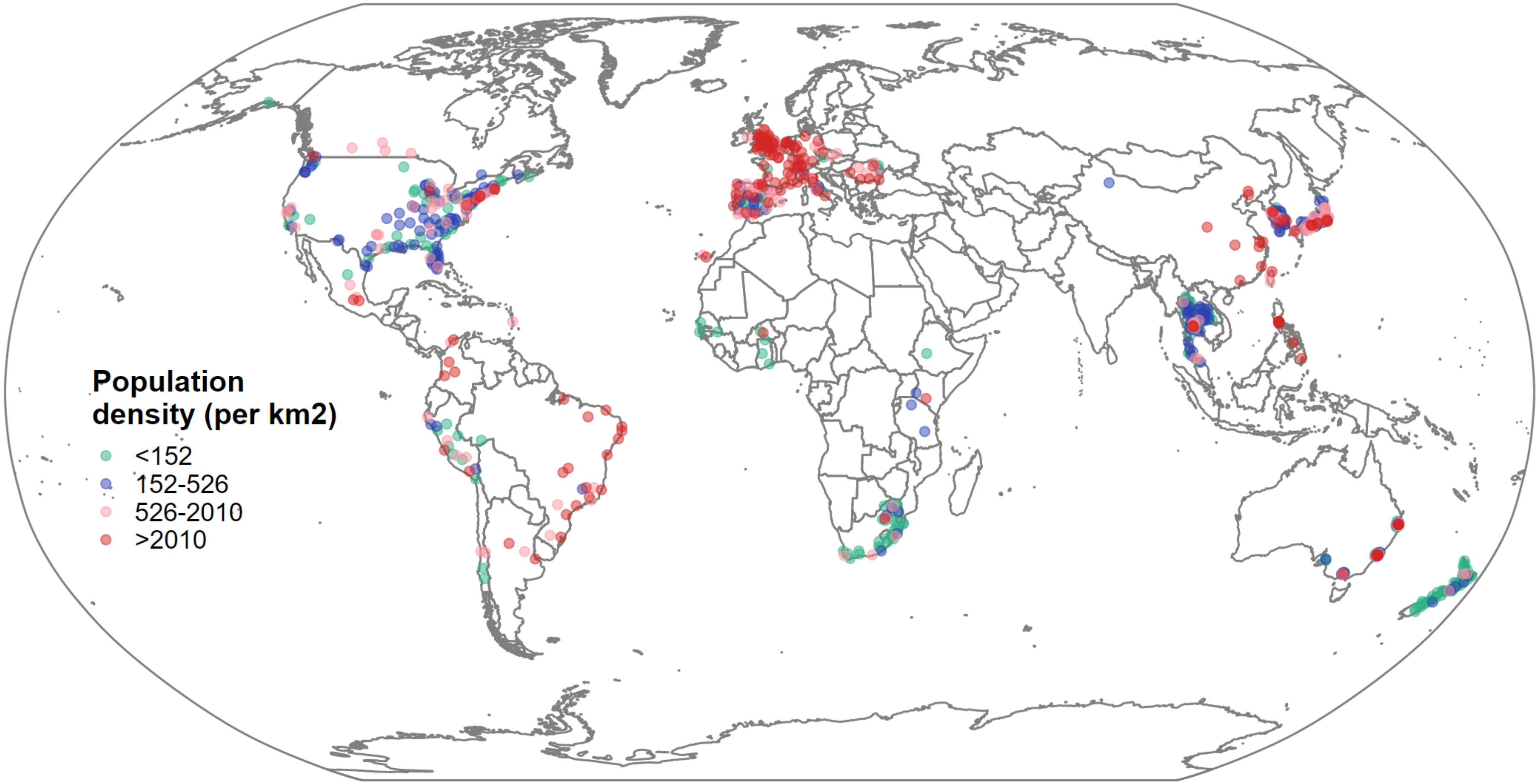

Figure S3. Population densities in the 761 communities.

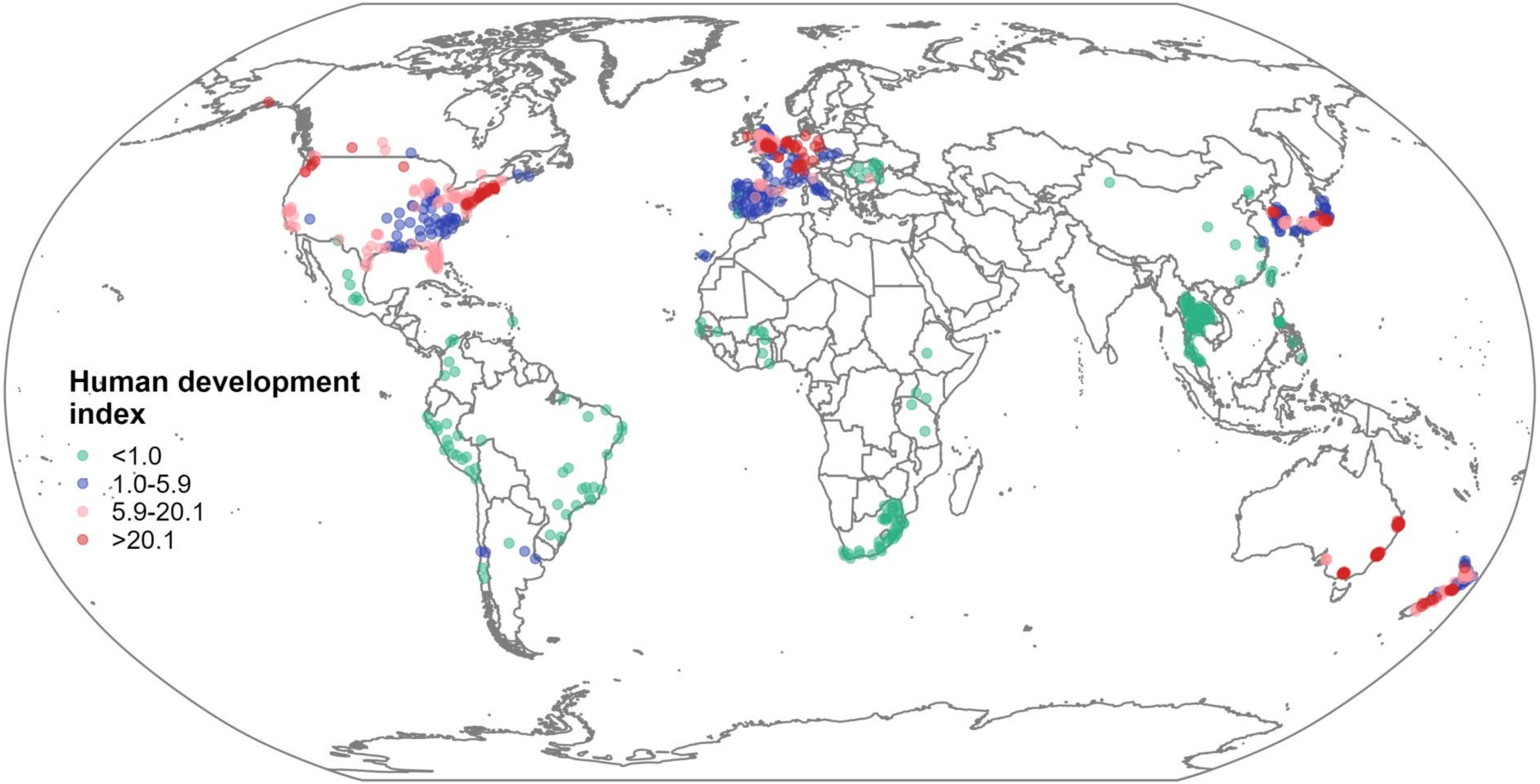

Figure S4. Human development indexes in the 761 communities.

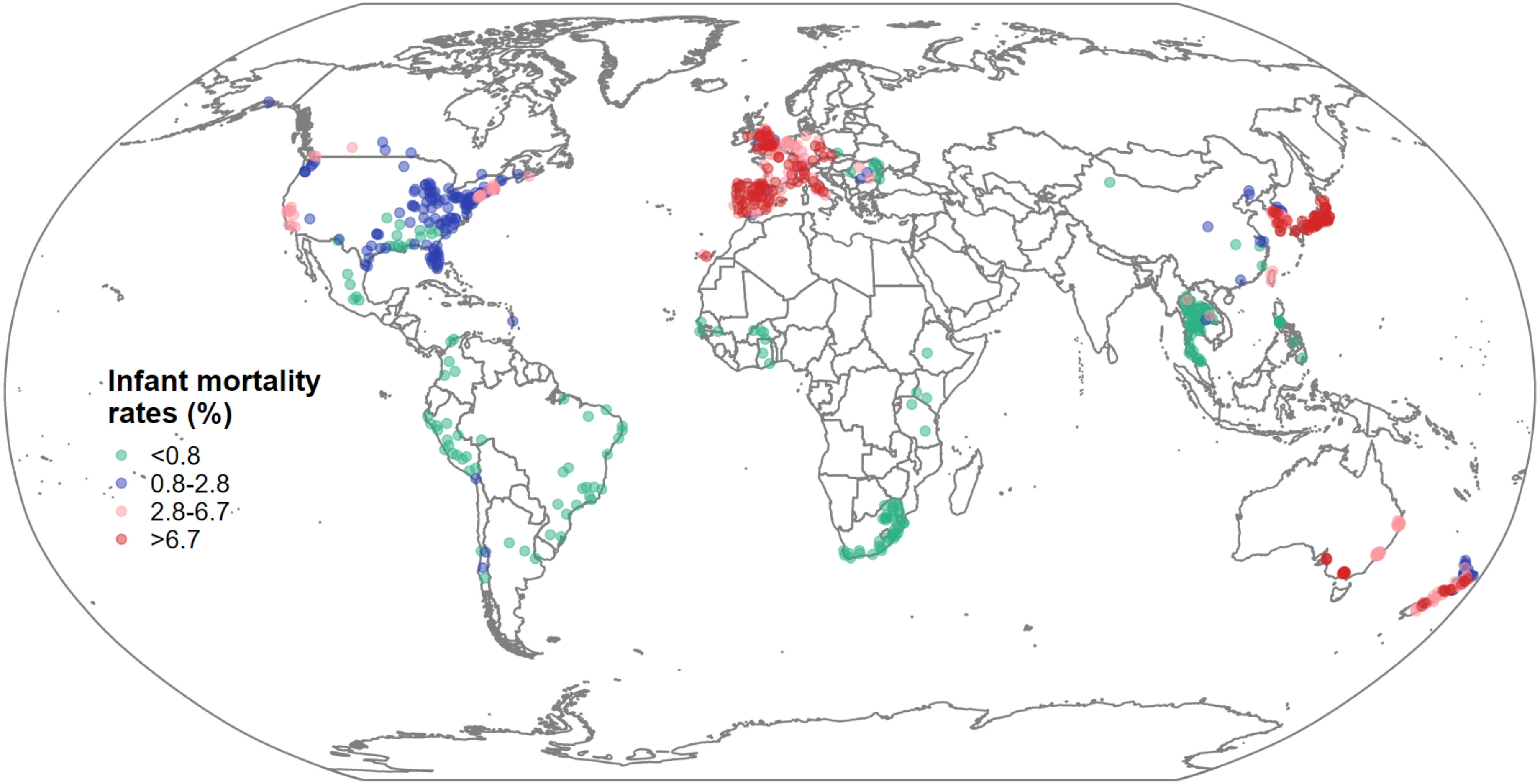

Figure S5. Infant mortality rates in the 761 communities.

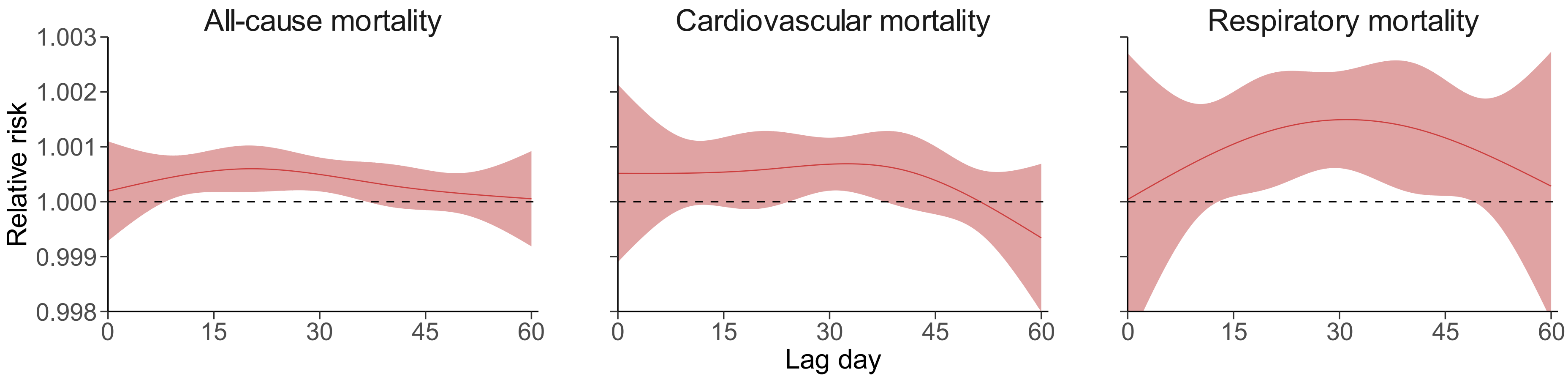

Figure S6. Relative risks of mortality associated with exposure to floods during lag 0-60 days in 761 communities. The lag-response association is modeled using a natural cubic B-spline with four degrees of freedom through a crossbasis function

MCC Collaborative Research Network
Rosana Abrutzky[1], Micheline de Sousa Zanotti Stagliorio Coelho Coelho[2], Paulo Hilario Nascimento Saldiva[3], Nicolás Valdés Ortega[4], Patricia Matus Correa[4], Haidong Kan[5], Samuel Osorio[6], Aleš Urban[7,8], Francesco Sera[9], Mathilde Pascal[10], Alexandra Schneider[11], Veronika Huber[12,13], Ariana Zeka[14], Patrick Goodman[15], Francesca de'Donato[16], Paola Michelozzi[16], Masahiro Hashizume[17], Yoonhee Kim[18], César De la Cruz Valencia[19], Magali Hurtado Diaz[19], Ala Overcenco[20], Caroline Ameling[21], Danny Houthuijs[21], Gabriel Carrasco-Escobar[22,23], Xerxes Seposo[24], Baltazar Nunes[25,26], Iulian-Horia Holobaca[27], Ana Maria Vicedo-Cabrera[28,29,30], Aurelio Tobias[31,24], Jouni J. K. Jaakkola[32,33], Yasushi Honda[34], Fiorella Acquaotta[35], Noah Scovronick[36], Ho Kim[37], Whanhee Lee[38,39], Carmen Íñiguez[40,41], Martina S. Ragettli[42,43], Shih-Chun Pan[44], Yue Leon Guo[45,44,46], Antonella Zanobetti[47], Joel Schwartz[47], Simon Hales[48]

[1]Universidad de Buenos Aires, Facultad de Ciencias Sociales, Instituto de Investigaciones Gino Germani, [2]Department of Pathology, Faculty of Medicine, University of São Paulo, São Paulo, Brazil, [3]INSPER, São Paulo, Brazil, [4]Department of Public Health, Universidad de los Andes, Santiago, Chile, [5]Department of Environmental Health, School of Public Health, Fudan University, Shanghai, China, [6]Department of Environmental Health, University of São Paulo, São Paulo, Brazil, [7]Institute of Atmospheric Physics, Czech Academy of Sciences, Prague 141 00, Czech Republic, [8]Faculty of Environmental Sciences, Czech University of Life Sciences, Prague, Czech Republic, [9]Department of Statistics, Computer Science and Applications "G. Parenti", University of Florence, Florence, Italy, [10]Santé Publique France, Department of Environmental and Occupational Health, French National Public Health Agency, Saint Maurice 94 410, France, [11]Institute of Epidemiology, Helmholtz Zentrum München – German Research Center for Environmental Health (GmbH), Neuherberg, Germany, [12]IBE-Chair of Epidemiology, LMU Munich, Munich, Germany, [13]Department of Physical, Chemical and Natural Systems, Universidad Pablo de Olavide, Sevilla, Spain, [14]Institute for the Environment, Brunel University London, London, UK, [15]Technological University Dublin, Ireland, [16]Department of Epidemiology, Lazio Regional Health Service, Rome, Italy, [17]Department of Global Health Policy, Graduate School of Medicine, The University of Tokyo, Tokyo, Japan, [18]Department of Global Environmental Health, Graduate School of Medicine, University of Tokyo, Tokyo, Japan, [19]Department of Environmental Health, National Institute of Public Health, Cuernavaca, Morelos, Mexico, [20]National Agency for Public Health of the Ministry of Health, Labour and Social Protection of the Republic of Moldova, [21]National Institute for Public Health and the Environment (RIVM), Centre for Sustainability and Environmental Health, Bilthoven, Netherlands, [22]Health Innovation Laboratory, Institute of Tropical Medicine “Alexander von Humboldt”, Universidad Peruana Cayetano Heredia, Lima, Peru, [23]Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA, USA, [24]School of Tropical Medicine and Global Health, Nagasaki University, Nagasaki, Japan, [25]Department of Epidemiology, Instituto Nacional de Saúde Dr Ricardo Jorge, [26]Centro de Investigação em Saúde Pública, Escola Nacional de Saúde Pública, Universidade NOVA de Lisboa, Lisboa, Portugal, [27]Faculty of Geography, Babes-Bolay University, Cluj-Napoca, Romania, [28]Institute of Social and Preventive Medicine, University of Bern, Bern, Switzerland, [29]Oeschger Center for Climate Change Research, University of Bern, Bern, Switzerland, [30]Department of Public Health Environments and Society, London School of Hygiene and Tropical Medicine, London, United Kingdom, [31]Institute of Environmental Assessment and Water Research (IDAEA), Spanish Council for Scientific Research (CSIC), Barcelona, Spain, [32]Center for Environmental and Respiratory Health Research (CERH), University of Oulu, Oulu, Finland, [33]Medical Research Center Oulu (MRC Oulu), Oulu University Hospital and University of Oulu, Oulu, Finland, [34]Center for Climate Change Adaptation, National Institute for Environmental Studies, Tsukuba, Japan, [35]Department of Earth Sciences, University of Torino, Italy, [36]Gangarosa Department of Environmental Health. Rollins School of Public Health, Emory University, Atlanta, USA, [37]Graduate School of Public Health, Seoul National University, Seoul, Republic of Korea,

[38]School of the Environment, Yale University, New Haven CT, USA, [39]Department of Occupational and Environmental Medicine, School of Medicine, Ewha Womans University, Seoul, South Korea, [40]Department of Statistics and Computational Research. Universitat de València, València, Spain, [41]Ciberesp, Madrid. Spain, [42]Swiss Tropical and Public Health Institute, Basel, Switzerland, [43]University of Basel, Basel, [44]National Institute of Environmental Health Science, National Health Research Institutes, Zhunan, Taiwan, [45]Environmental and Occupational Medicine, National Taiwan University (NTU) College of Medicine and NTU Hospital, Taipei, Taiwan, [46]Graduate Institute of Environmental and Occupational Health Sciences, NTU College of Public Health, Taipei, Taiwan, [47]Department of Environmental Health, Harvard T.H. Chan School of Public Health, Boston, MA, USA, [48]Department of Public Health, University of Otago, Wellington, New Zealand

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