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Comparison for the effects of different components of temperature variability on mortality: A multi-country time-series study

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ABSTRACT

Background: Temperature variability (TV) is associated with increased mortality risk. However, it is still unknown whether intra-day or inter-day TV has different effects.
Objectives: We aimed to assess the association of intra-day TV and inter-day TV with all-cause, cardiovascular, and respiratory mortality.
Methods: We collected data on total, cardiovascular, and respiratory mortality and meteorology from 758 locations in 47 countries or regions from 1972 to 2020. We defined inter-day TV as the standard deviation (SD) of daily mean temperatures across the lag interval, and intra-day TV as the average SD of minimum and maximum temperatures on each day. In the first stage, inter-day and intra-day TVs were modelled simultaneously in the quasi-Poisson time-series model for each location. In the second stage, a multi-level analysis was used to pool the location-specific estimates.
Results: Overall, the mortality risk due to each interquartile range [IQR] increase was higher for intra-day TV than for inter-day TV. The risk increased by 0.59% (95% confidence interval [CI]: 0.53, 0.65) for all-cause mortality, 0.64% (95% CI: 0.56, 0.73) for cardiovascular mortality, and 0.65% (95% CI: 0.49, 0.80) for respiratory mortality per IQR increase in intra-day $TV_{0–7}$ (0.9 °C). An IQR increase in inter-day $TV_{0–7}$ (1.6 °C) was associated with 0.22% (95% CI: 0.18, 0.26) increase in all-cause mortality, 0.44% (95% CI: 0.37, 0.50) increase in cardiovascular mortality, and 0.31% (95% CI: 0.21, 0.41) increase in respiratory mortality. The proportion of all-cause deaths attributable to intra-day $TV_{0–7}$ and inter-day $TV_{0–7}$ was 1.45% and 0.35%, respectively. The mortality risks varied by lag interval, climate area, season, and climate type.
Conclusions: Our results indicated that intra-day TV may explain the main part of the mortality risk related to TV and suggested that comprehensive evaluations should be proposed in more countries to help protect human health.

1. Introduction

Interest in understanding the health impacts of short-term temperature variations has grown in recent decades, as human-induced climate change is increasing the unstable weather conditions in both frequency and intensity across the globe (Guoet al., 2021; IPCC, 2012;

Stott, 2016). Studies have reported that increased mortality and morbidity risk was associated with temperature variability (TV), which is defined as the standard deviation of daily maximum and minimum temperatures during several days (Guoet al., 2016; Zhaoet al., 2018; Zhaoet al., 2019). Another two indices of temperature variation frequently used in previous studies were diurnal temperature range (DTR, defined as the difference between daily maximum and minimum temperatures) and temperature change between the neighbouring days (TCN, defined as the difference between daily mean temperatures of two neighbouring days) (Chenget al., 2014; Leeet al., 2018; Linet al., 2013; Maet al., 2020).

Some studies have reported potential differentiated effects of temperature variation within the same day or between neighbouring days by using DTR and TCN as indicators for intra-day and inter-day temperature variation (Hu, 2021; Vicedo-Cabreraet al., 2016). However, there are some limitations. First, only absolute changes in temperature were considered in definitions of DTR or TCN and therefore the effect estimates of the two indicators were not comparable. Second, DTR can only capture the temperature change within one single day. Similarly, TCN can only capture the temperature change within two neighbouring days. These two indicators, however, are unable to measure the temperature variation during a longer period (≥3 days). This may hinder the comprehensive evaluation of health impacts associated with temperature variation. Compared with DTR and TCN, TV has been identified as a better metric to represent temperature variation, as temperature variation is a continuous process and evaluating its impact within a short exposure window (e.g., from two days to seven days) could provide a more comprehensive view (Guoet al., 2016). It is therefore helpful to apply the same framework to define the inter-day and intra-day TV and to further compare their impacts.

In this study, we applied two novel indicators proposed by us recently, intra-day TV and inter-day TV (Wenet al., 2023), to reveal the mortality risk associated with different components of TV. A global analysis within the Multi-Country Multi-City (MCC) Collaborative Research Network was performed to assess the association of intra-day TV and inter-day TV with all-cause, cardiovascular, and respiratory mortality in 758 locations of 47 countries or regions. Following the most comprehensive and standardized analytical framework, we aimed to investigate the health impacts of intra-day and inter-day TVs at the global, regional, and country-level and to further identify potentially vulnerable or susceptible areas.

2. Methods

2.1. Data collection

Mortality data and meteorological data were obtained from the MCC Collaborative Research Network (https://mccstudy.lshtm.ac.uk/), which has been described in detail in previous studies (Gasparriniet al., 2015; Liuet al., 2019). A total of 758 locations from 47 countries or regions were included in the present study. Generally, we obtained daily counts of mortality data from local authorities of each country or region. We classified causes of death using the international classification of diseases, 9th and 10th revision (ICD-9 and ICD-10) codes, where available. In each location, mortality data for non-external causes (ICD-9: 0–799; ICD-10: A0-R99) were collected while all-cause mortality data were alternatively collected if data on non-external causes were unavailable. We also collected daily counts of mortality specifically for cardiovascular (ICD-10: I00-I99) and respiratory causes (ICD-10: J00-J99). Daily weather data including daily minimum, mean, and maximum temperatures and relative humidity (RH) were collected from local meteorological bureaus or other statistical authorities. Detailed descriptions of data and missing values were provided in the supplementary eMethods.

2.2. Definition of inter-day and intra-day temperature variability

In this study, we applied a new definition for inter-day and intra-day TV, computing these indices as the standard deviation (SD) of daily minimum, mean, and maximum temperatures within the lag intervals (Guoet al., 2016; Xuet al., 2020). Details are provided in our previous study(Wenet al., 2023). Briefly, we computed inter-day TV as the SD of daily mean temperature during 0–L lag days, and intra-day TV as the average SD of minimum temperature and maximum temperature on each day, which was calculated as follows:

$$TV_{intra-day,0-L} = \sqrt{\frac{\sum VAR_l}{2L+1}}$$

$$TV_{inter-day,0-L} = \sqrt{\frac{2L \times VAR_{tmean}}{2L+1}}$$

where L is the number of preceding days defining the lag interval (e.g., $L = 1$ when calculating TV_{0-1}, $L = 2$ when calculating TV_{0-2}, and so on), VAR_l is the variance of daily temperature deviations on lag day l, VAR_{tmean} is the variance of daily mean temperatures within the lag interval. The inter-day TV and intra-day TV could be regarded as components of TV defined in our previous studies because they have the following relationship:

$$TV_{0-L} = \sqrt{TV_{inter-day,0-L}{}^2 + TV_{intra-day,0-L}{}^2}$$

Consistent with the previous definition, both inter-day and intra-day TV could account for the lag effects (Guoet al., 2016; Xuet al., 2020). Following these studies, we used inter-day and intra-day TV_{0-1} to TV_{0-7} as the temperature variability exposure.

2.3. Statistical analyses

We assessed the associations of mortality with inter-day TV and intra-day TV using a two-stage analytical framework, which has been widely applied in previous multi-center time-series studies (Bellet al., 2005; Gasparriniet al., 2012; Liuet al., 2019). Briefly, a same time-series model was applied for each location and location-specific estimates were then pooled through meta-analyses.

2.3.1. ***Main*** *analyses*

In the first stage, we used a generalized linear regression model with quasi-Poisson family in each location to obtain location-specific estimates. Location-specific daily all-cause or cause-specific mortality counts were treated as the dependent variable in separate models. We simultaneously modelled inter-day TV and intra-day TV using linear functions according to previous studies (Guoet al., 2016; Wenet al., 2023; Xuet al., 2020). In each model, we adjusted for daily mean temperature using a distributed lag non-linear model (DLNM) (Gasparriniet al., 2010). A natural cubic spline with four degrees of freedom was applied for both exposure–response dimension and lag dimension up to 21 days (equally-spaced knots in the log scale of lag days) in the cross-basis function of daily mean temperature (Guoet al., 2016). We also controlled long-term trend and seasonal variations in the model by adding a natural cubic spline of time with seven degrees of freedom (df) per year, and controlled the effects of day of the week by adding an indicator variable for day of the week.

In the second stage, a random-effects multilevel meta-analytical method was applied to pool the location-specific estimations under a hierarchical structure (locations and countries/regions) (Seraet al., 2019). Best linear unbiased predictions (BLUP) were used to obtain location-specific and country-specific associations between mortality with inter-day TV and intra-day TV, which can borrow strength across units within the same level and provide more precise estimations, especially for locations with small data size (Chenet al., 2021; Vicedo-

Cabreraet al., 2020). We also examined the heterogeneity across locations using the Cochran Q test and I^2 statistic. We used fixed effect meta-regressions to test the statistical differences in effect estimations for inter-day TV and intra-day TV (Xuet al., 2019).

The associations of mortality with inter-day TV and intra-day TV were reported as percentage change associated with per interquartile range (IQR) increase of location-specific inter-day TV or intra-day TV and 95 % confidence intervals (95 % CI). We further computed the fractions of deaths attributable to inter-day TV and intra-day TV (above the minimum TV). First, the location-specific number of deaths attributable to inter-day TV or intra-day TV was calculated using pooled effect estimates of 758 locations. Then, the attributable number of deaths in each location was summed to the country-level and the global level, and were then divided by the total number of deaths at each level to derive the attributable fractions (AF) with 95 % CIs. The calculation procedures are shown in detail in the supplementary eMethods.

2.3.2. Stratified analyses

First, we divided 758 locations into four climate groups (cold, moderate cold, moderate warm, and warm areas) by the quantiles of annual mean temperatures (≤25th [10.6 °C], 25th–50th [13.9 °C], 50th–75th [18.8 °C], and ≥75th) during the study period. We pooled the location-specific estimates using a random-effect multilevel meta-analysis to obtain associations in four groups. Second, we examined the associations of mortality with inter-day TV or intra-day TV in different seasons. Stratified analyses were conducted for cold season (4 coldest months), warm season (4 hottest months), and moderate season (other months). The seasons were defined using monthly mean temperatures in each location. Besides, we performed the stratified analyses in Köppen-Geiger climate groups. The Köppen-Geiger climate system divides the locations into five main groups: tropical, dry, temperate, continental, and polar.

2.3.3. Sensitivity analyses

Several sensitivity analyses were conducted to assess the robustness of our results. First, associations of mortality with inter-day TV or intra-day TV were expressed as the relative risk associated with per 1 °C increase in inter-day or intra-day TV. Secondly, lag days of daily mean

Table 1
Summary of study periods, number of deaths, median (IQR) of inter-day and intra-day TV in each country/region.

Country/region	No of locations	Period	Number of deaths (in thousands)			TV, Median (IQR)	
			Total	Cardiovascular	Respiratory	Inter-day TV (°C)	Intra-day TV (°C)
Argentina	3	2005–2015	686.3	NA	NA	2.6 (2.5, 2.7)	6.3 (5.1, 6.8)
Australia	3	1988–2009	1,178.00	NA	NA	1.7 (1.4, 2.4)	4.5 (4.2, 4.7)
Brazil	17	1997–2018	3,822.60	1,201.00	452.8	1.2 (0.9, 1.8)	5.2 (4.2, 5.8)
Canada	26	1986–2015	3,733.70	1,264.60	316.5	3.2 (2.9, 3.5)	5.1 (4.5, 5.7)
Chile	4	2004–2014	325.5	NA	NA	1.5 (0.9, 1.6)	5.6 (3.3, 6.3)
China	15	1996–2015	1,069.20	411.9	144.7	2.1 (1.9, 2.2)	5.1 (3.4, 5.7)
Colombia	5	1998–2013	956.5	267.9	99.8	0.8 (0.7, 0.9)	5.0 (3.8, 5.4)
Costa Rica	1	2000–2017	31.1	9.3	2.7	0.8 (0.8, 0.8)	4.5 (4.5, 4.6)
Czech Republic	4	1994–2015	711.9	360	39.9	2.6 (2.5, 2.7)	3.2 (3.0, 3.3)
Ecuador	2	2014–2018	112.3	32.8	13	0.9 (0.8, 1.0)	4.9 (3.7, 6.2)
Estonia	5	1997–2018	167.8	85.7	5.6	2.4 (2.3, 2.6)	4.2 (3.9, 4.4)
Finland	1	1994–2014	153.3	57.4	9.7	2.3 (2.1, 2.3)	3.4 (3.4, 3.6)
France	18	2000–2015	1,753.60	NA	109.9	2.1 (1.9, 2.3)	4.8 (4.1, 5.1)
French Caribbean	2	2000–2015	46.2	NA	NA	0.6 (0.6, 0.6)	3.8 (3.5, 3.9)
French Guiana	1	2000–2015	7.1	NA	NA	0.6 (0.5, 0.6)	4.1 (4.0, 4.2)
Réunion	1	2000–2015	13.9	NA	NA	0.7 (0.6, 0.7)	3.5 (3.4, 3.6)
Germany	12	1993–2015	3,105.90	NA	NA	2.3 (2.2, 2.4)	4.5 (4.3, 4.7)
Greece	1	2001–2010	288	136.2	28.8	1.8 (1.7, 1.8)	4.1 (4.0, 4.3)
Guatemala	1	2009–2016	62.7	NA	NA	0.9 (0.9, 1.0)	4.8 (4.6, 4.8)
Iran	2	2002–2015	817.9	357.7	59.4	2.2 (2.1, 2.3)	5.5 (5.2, 6.7)
Ireland	6	1984–2007	1,058.20	340.3	164.1	1.6 (1.5, 1.8)	3.6 (3.2, 3.9)
Israel	1	1985–2020	350.6	NA	NA	1.4 (1.3, 1.5)	5.7 (5.6, 5.9)
Italy	11	1987–2010	820.4	NA	NA	1.5 (1.4, 1.6)	4.4 (3.7, 4.9)
Japan	47	1972–2015	39,917.60	13,631.40	5,028.30	1.8 (1.7, 1.9)	4.5 (4.1, 5.0)
Kuwait	1	2000–2016	73.7	35.3	5.7	1.3 (1.3, 1.3)	4.3 (4.3, 4.4)
Mexico	10	1998–2014	2,980.10	765.2	284.2	1.4 (1.0, 1.9)	7.0 (6.2, 7.5)
Moldova	4	2001–2010	59.9	NA	NA	2.5 (2.4, 2.6)	5.2 (4.7, 5.7)
Netherland	5	1995–2016	453.4	NA	NA	2.1 (2.0, 2.2)	4.2 (4.0, 4.5)
Norway	1	1979–2018	212.1	79.8	21.1	2.2 (2.1, 2.3)	3.8 (3.7, 3.9)
Panama	1	2013–2016	11.5	3.9	1	0.8 (0.8, 0.8)	4.0 (3.9, 4.1)
Paraguay	1	2004–2019	48	15.4	4.4	2.7 (2.7, 2.8)	5.7 (5.6, 5.7)
Peru	18	2008–2014	633.1	NA	NA	0.9 (0.8, 1.0)	6.2 (5.1, 7.2)
Philippines	13	2006–2019	821.5	296.9	118.5	0.6 (0.6, 0.7)	2.8 (2.7, 2.8)
Portugal	6	1980–2018	1,925.30	718.6	181.4	1.8 (1.6, 1.9)	5.0 (4.6, 5.7)
Puerto Rico	1	2009–2016	26.6	NA	NA	0.7 (0.7, 0.7)	3.5 (3.4, 3.6)
Romania	8	1994–2016	951.1	NA	NA	2.3 (2.2, 2.5)	5.6 (5.2, 6.1)
South Africa	52	1997–2013	8,509.10	1,299.70	1,046.90	2.0 (1.7, 2.4)	7.5 (6.8, 8.4)
South Korea	36	1997–2018	3,070.40	701.6	222.3	2.1 (1.9, 2.2)	5.3 (4.4, 6.1)
Spain	52	1990–2014	3,017.10	1,042.00	340.5	1.7 (1.4, 1.9)	5.1 (3.6, 5.7)
Sweden	3	1990–2016	717.3	310.8	54.9	1.9 (1.8, 2.0)	3.6 (3.4, 3.8)
Switzerland	8	1995–2013	243.6	90.7	16	2.2 (2.0, 2.3)	4.1 (3.7, 4.5)
Taiwan	3	1994–2014	1,209.60	269.4	116.5	1.5 (1.3, 1.8)	3.7 (3.4, 4.4)
Thailand	62	1999–2008	1,827.90	338.6	225.4	0.9 (0.7, 1.1)	5.2 (4.6, 5.6)
UK	70	1990–2016	6,167.10	2,258.30	910.4	1.7 (1.6, 1.9)	3.3 (2.8, 3.5)
Uruguay	1	2012–2016	153.6	NA	NA	2.3 (2.2, 2.3)	4.1 (4.1, 4.3)
USA	211	1979–2006	32,194.90	11,482.40	2,941.50	2.8 (2.2, 3.1)	5.1 (4.5, 5.6)
Vietnam	2	2009–2013	108.2	24.4	9	1.3 (0.8, 1.4)	4.4 (4.3, 4.5)
Pooled	758	1972–2020	126,605.10	37,889.30	12,975.00	2.0 (1.7, 2.6)	4.9 (3.9, 5.5)

Note. NA means data are unavailable in this country or region.

temperature in our models were changed from 21 to 28. Thirdly, we also changed the degrees of freedom for daily mean temperature (3, 4, 5, and 6 df). Fourth, we used daily minimum temperature or daily maximum temperature to replace the daily mean temperature in our models using the same cross-basis function. Fifth, we adjusted for RH in our models to assess whether RH could confound the associations using the same DLNM model as daily mean temperature. In addition, we performed separate models by including only one of TV indicators (inter-day TV and intra-day TV) to check whether the associations were confounded by themselves. Finally, we further examined the temporal trends in mortality risk linked to inter-day and intra-day TV by dividing the study period into distinct groups: 1972–1980, 1981–1990, 1991–2000, 2001–2010, and 2011–2020. All the analyses were performed by R software (V4.0.3). The "dlnm" package was used to perform the distributed lag linear models and the 'mixmeta' package was used to perform the meta-regression models.

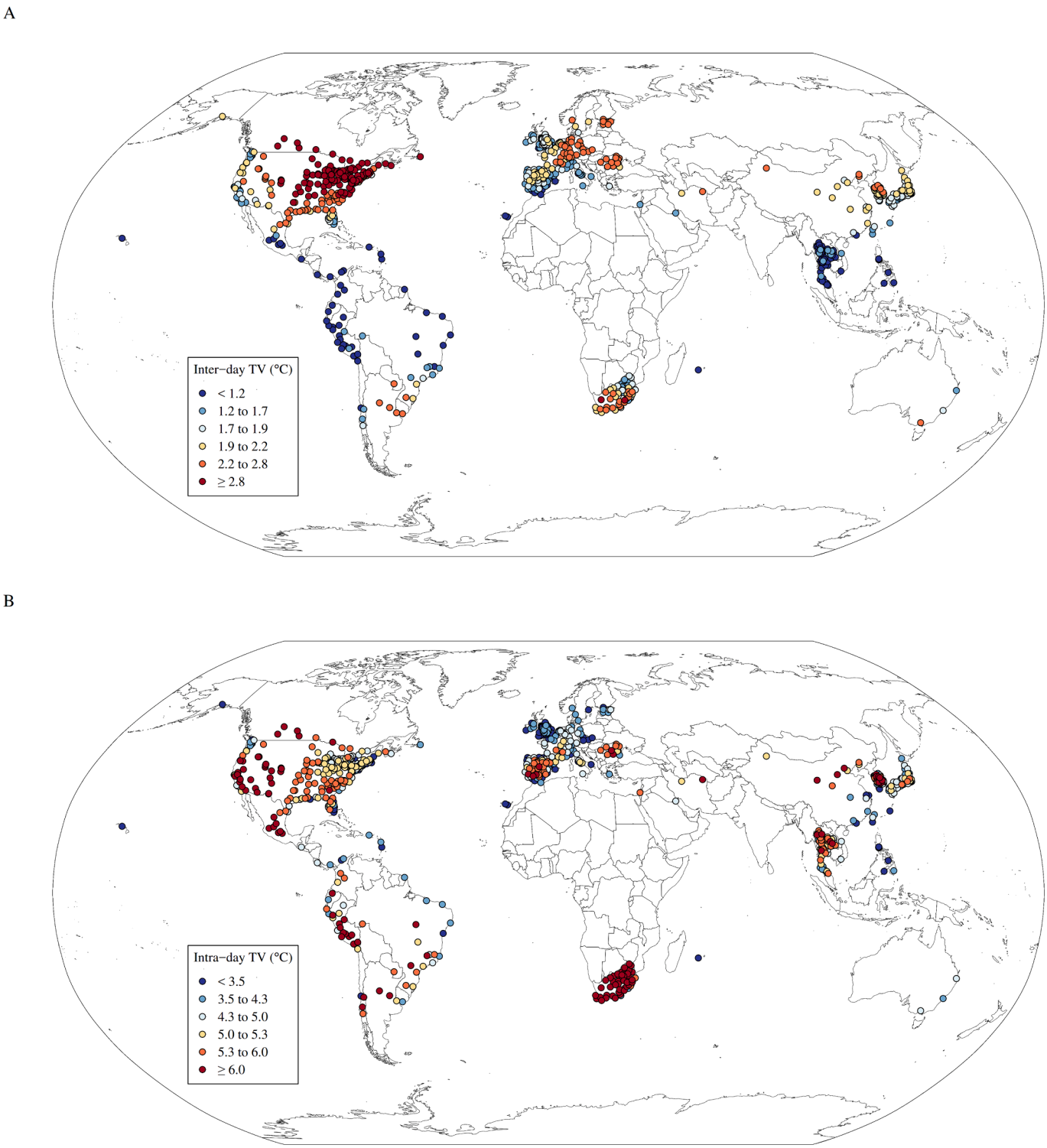


Fig. 1. Location of study areas and mean values of inter-day and intra-day temperature variability (°C, TV_{0-7}).

3. Results

3.1. Descriptive statistics

This study included a total of 126.6 million deaths in 758 locations of 47 countries or regions covering an average period from 1972 to 2020, including 37.9 million cardiovascular deaths and 13.0 million respiratory deaths (Table 1). Overall, the median inter-day $TV_{0–7}$ was 2.0 °C (interquartile range [IQR]: 1.7 °C, 2.6 °C), which was lower than the median intra-day $TV_{0–7}$ (4.9 °C; IQR: 3.9 °C, 5.5 °C). The summary of inter-day and intra-day TV0–1 to TV0–7 and the proportion of zero death counts are presented in supplementary Table S1 and S2. Fig. 1 shows the average inter-day $TV_{0–7}$ and the average intra-day $TV_{0–7}$ in each location. The highest inter-day $TV_{0–7}$ were mainly observed for locations in the USA and Canada while the lowest levels were mainly observed in Southeast Asia and South America. By contrast, locations with the highest intra-day $TV_{0–7}$ were obtained mainly in South Africa and the USA while the lowest values were mainly observed in Western Europe.

3.2. TV-mortality associations

The pooled results of short-term TV-mortality associations across study locations are shown in Fig. 2. The results for test of heterogeneity across locations are shown in supplementary Table S3 and the exact values for Fig. 2 are shown in supplementary Table S4. On average, each IQR increase in intra-day $TV_{0–7}$ was associated with a 0.59 % increase in all-cause mortality (95 % CI: 0.53 %, 0.65 %), 0.64 % increase in cardiovascular mortality (95 % CI: 0.56 %, 0.73 %), and 0.65 % increase in respiratory mortality (95 % CI: 0.49 %, 0.80 %). The mortality risks associated with inter-day $TV_{0–7}$ were lower than the intra-day $TV_{0–7}$. An IQR increase in exposure to inter-day $TV_{0–7}$ elevated the all-cause mortality risk by 0.22 % (95 % CI: 0.18 %, 0.26 %), cardiovascular mortality risk by 0.44 % (95 % CI: 0.37 %, 0.50 %), and respiratory mortality risk by 0.31 % (95 % CI: 0.21 %, 0.41 %). The mortality risks for intra-day and inter-day $TV_{0–7}$ were the highest among all the lag intervals. The exact values of mortality risk for each country or region were shown in supplementary Table S5–S7.

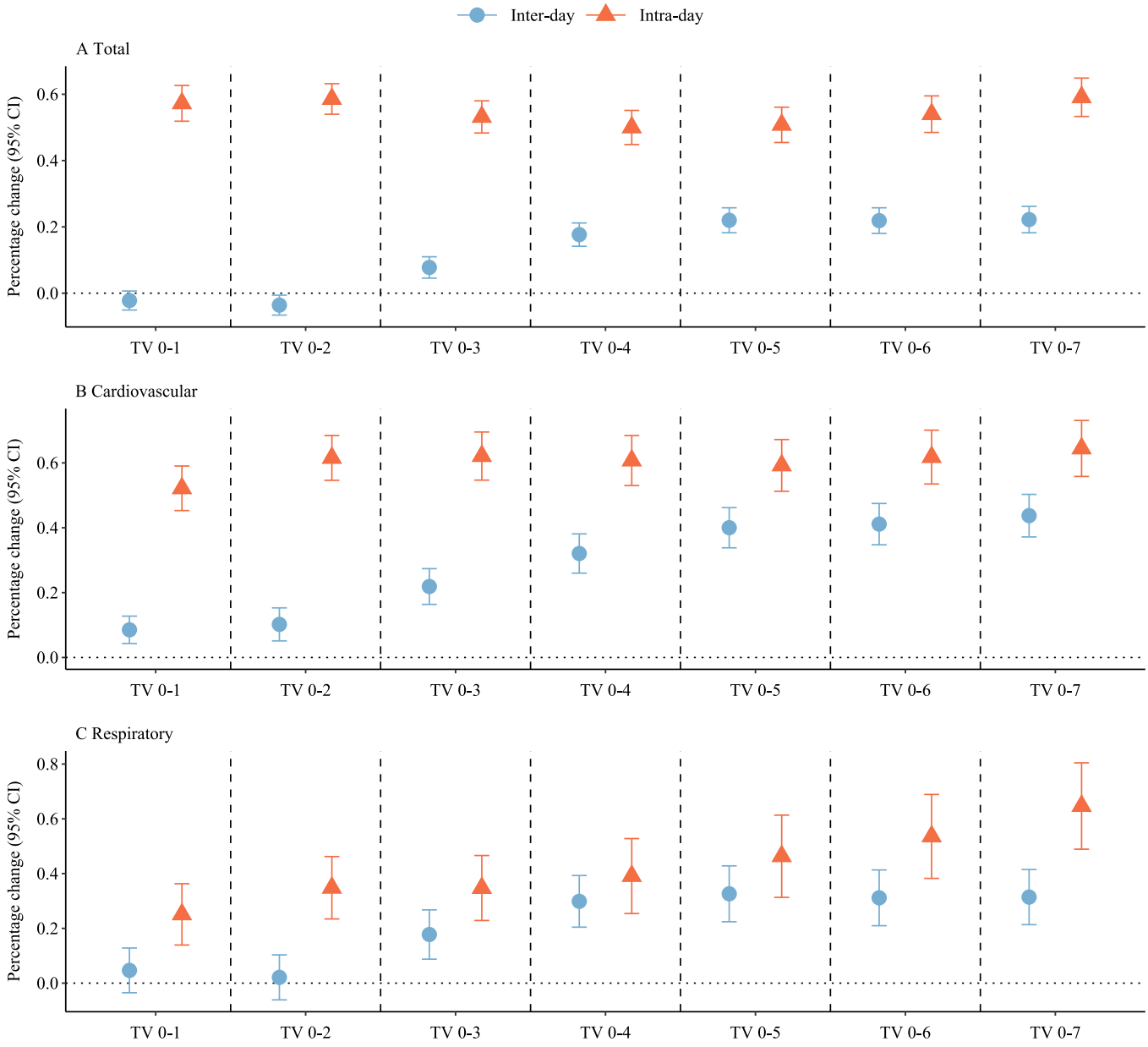


Fig. 2. Overall percentage change (%) of mortality risk over one interquartile range of inter-day and intra-day TV ($TV_{0–1}$ to $TV_{0–7}$).

3.3. *Stratified* results

Fig. 3 shows the stratified results by climate areas, seasons, and Köppen-Geiger climate groups. The mortality risks related to intra-day $TV_{0–7}$ were higher than the risks of inter-day $TV_{0–7}$ in all climate areas while the difference between mortality risk of inter-day and intra-day $TV_{0–7}$ was greater in the warm area. When stratified by season, lower mortality risks related to inter-day $TV_{0–7}$ were observed in the moderate season and warm season compared with intra-day $TV_{0–7}$, while inter-day $TV_{0–7}$ was associated with slightly higher mortality risk in the cold season. When examining the effect estimates in different Köppen-Geiger climate groups, the differences in mortality risk of inter-day and intra-day $TV_{0–7}$ were greater in the dry climate and the polar climate. The exact values of Fig. 3 were presented in supplementary Table S8–S16.

3.4. Geographical *variations*

Fig. 4 shows the mortality risks related to inter-day and intra-day $TV_{0–7}$ in each country (Fig. 4A) and each location (Fig. 4B and 4C). The highest mortality risks associated with intra-day $TV_{0–7}$ were found in Argentina, Greece, and Japan, whereas the lowest mortality risks were estimated for Ireland, Iran, and Chile. Referring to inter-day $TV_{0–7}$, the highest mortality risks were found in Costa Rica, Iran, and Japan, while the lowest mortality risks were found in Argentina, Guatemala, and Paraguay. The highest mortality risks of inter-day $TV_{0–7}$ and highest intra-day $TV_{0–7}$ were mainly observed for locations in North America and Japan, while the lowest levels were mainly observed in Europe and South Africa.

3.5. Attributable burden

Table 2 depicts the mortality fractions attributable to the exposure of intra-day $TV_{0–7}$ and inter-day $TV_{0–7}$ and Table 3 provides the annual average attributable deaths. The attributable fractions and the annual average attributable deaths of $TV_{0–1}$ to $TV_{0–6}$ are shown in supplementary Table S17–S22. Overall, a total of 1.45 % (95 % CI: 1.31 %, 1.60 %) and 0.35 % (95 % CI: 0.29 %, 0.41 %) of all-cause deaths were estimated to be attributable to intra-day $TV_{0–7}$ and inter-day $TV_{0–7}$ exposure across 758 locations, corresponding to 76,598 attributable deaths per year (95 % CI: 69,023, 84,160) for intra-day $TV_{0–7}$ and 17,120 attributable deaths per year (95 % CI: 14,170, 20,068) for inter-day $TV_{0–7}$. Specifically, 1.57 % (95 % CI: 1.35 %, 1.79 %) of cardiovascular mortality and 1.57 % (95 % CI: 1.18 %, 1.96 %) of respiratory mortality were associated with exposure to intra-day $TV_{0–7}$ while the percentages related to inter-day $TV_{0–7}$ exposure were 0.66 % (95 %CI: 0.56 %, 0.76 %) for cardiovascular mortality and 0.44 % (95 % CI: 0.28 %, 0.60 %) respiratory mortality. The attributable fractions varied substantially across different countries, with the largest fractions for all-cause mortality related to intra-day $TV_{0–7}$ observed in Iran, Romania, and South Africa. Referring to inter-day $TV_{0–7}$ exposure, Paraguay, Canada, and the Czech Republic had the highest attributable fractions for all-cause, cardiovascular, and respiratory mortality.

3.6. Sensitivity analyses

Sensitivity analyses show that our results were robust when we assessed the relative risk associated with per 1 °C increase in inter-day or intra-day TV, changed the lag days or the df the lag-response curve for daily mean temperatures, and when we used daily minimum temperature or daily maximum temperature to replace the daily mean temperature (supplementary Figure S1–S5). The results did not change substantially when we performed separate models by including only one of the TV indicators and when we adjusted for RH in our models (supplementary Figure S6 and S7). The temporal trends of mortality risk are

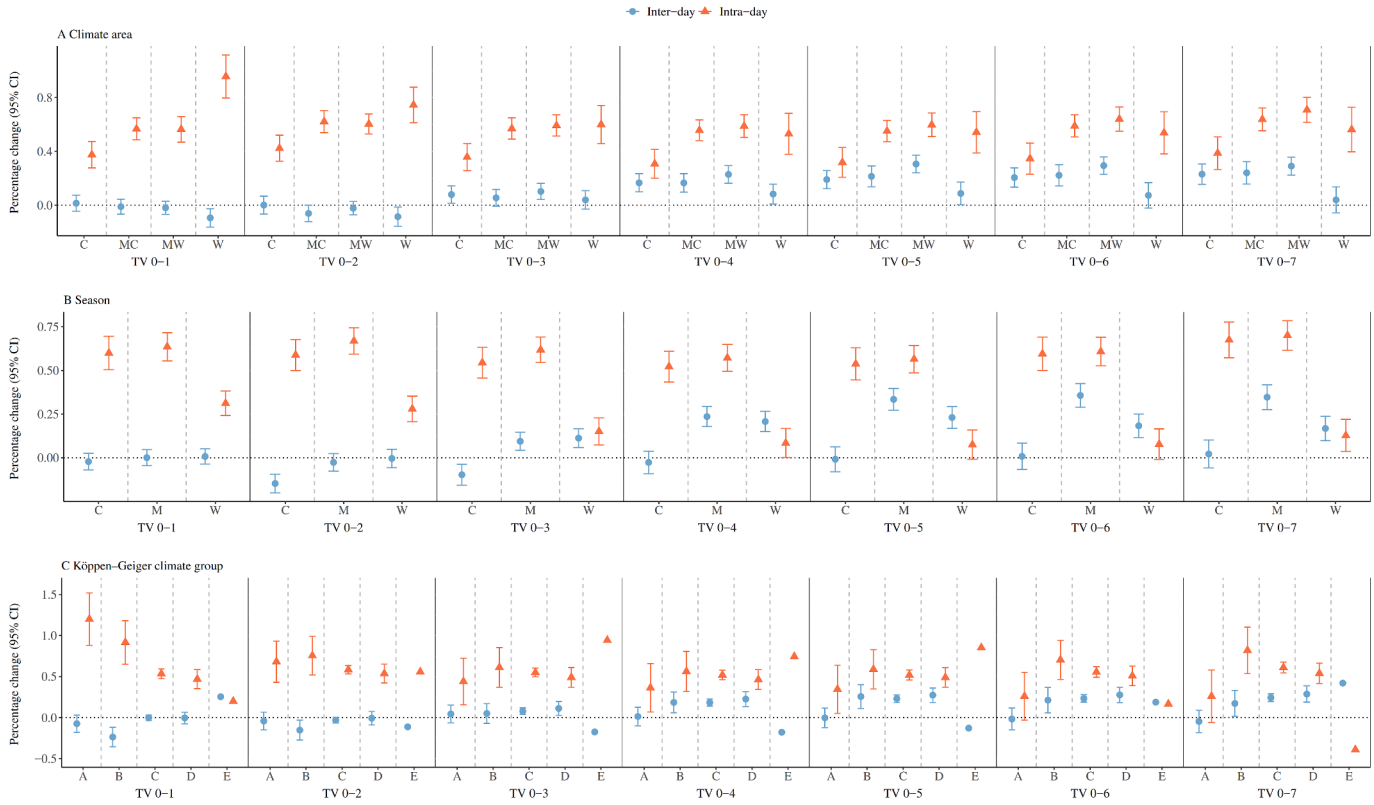


Fig. 3. Overall percentage change (%) of mortality risk for inter-day and intra-day TV ($TV_{0–1}$ to $TV_{0–7}$) in different climate areas (A), seasons (B), and Köppen–Geiger climate groups (C). Definition of abbreviations: (A) C = cold, MC = moderate cold, MW = moderate warm, W = warm; (B) C = cold, M = moderate, W = warm; (C) A = tropical, B = dry, C = temperate, D = continental, and E = polar.

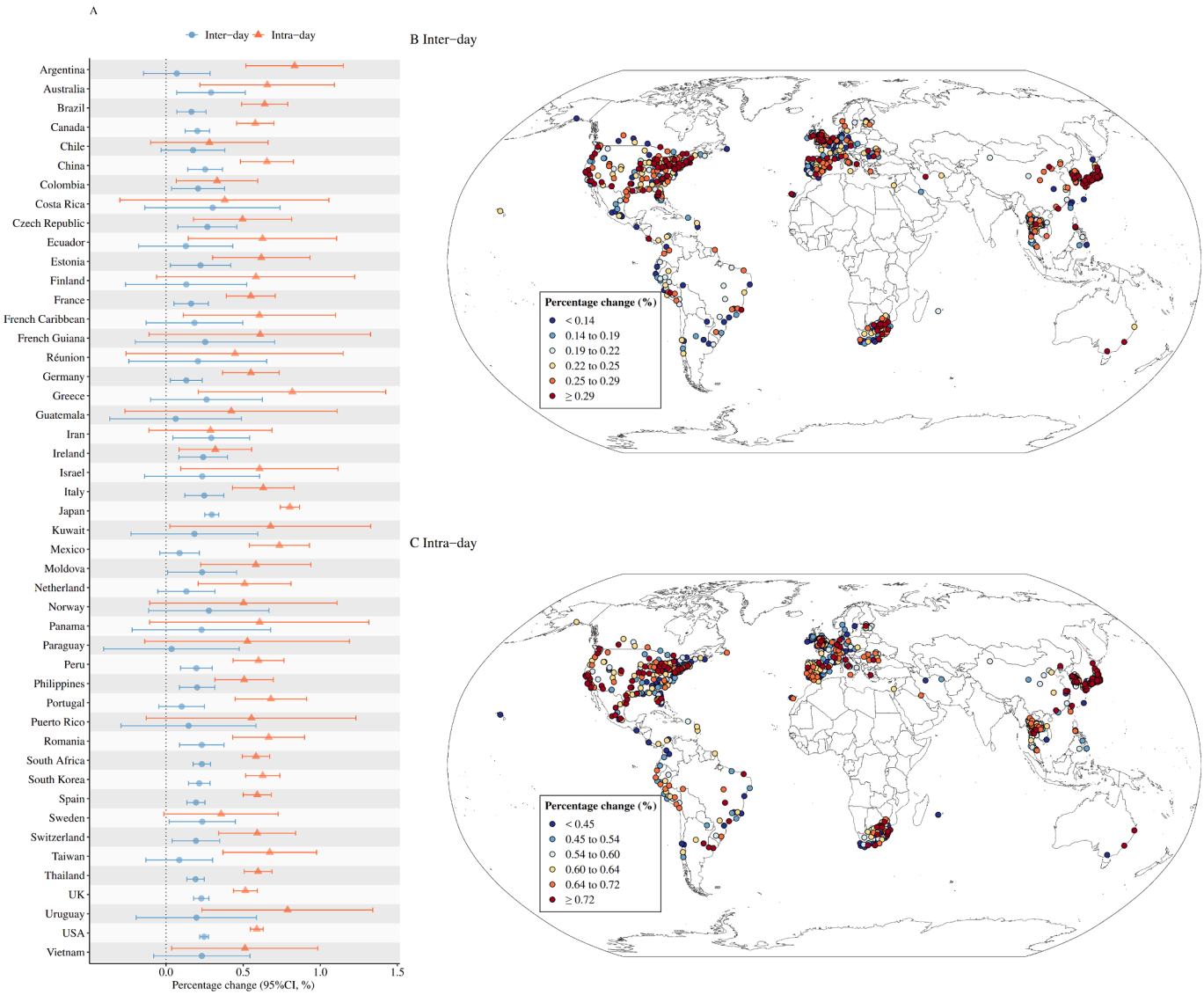


Fig. 4. Overall percentage change (%) of mortality risk for inter-day and intra-day TV_{0-7} in all countries/regions (A) and locations (B and C).

presented in supplementary Figure S8, showing there is a decrease in the mortality risk associated with both inter-day and intra-day TV over the study period.

4. Discussion

To the best of our knowledge, this is the first and largest study to investigate the associations of daily mortality with intra-day TV and inter-day TV on a global scale. Generally, increased risks for all-cause, cardiovascular, and respiratory mortality were observed to be significantly associated with exposure to inter-day and intra-day TVs. We estimated that a total of 1.45 % and 0.35 % of all-cause deaths could be attributed to intra-day TV_{0-7} and inter-day TV_{0-7}, corresponding to 76,598 and 17,120 annual average attributable deaths, respectively. We found that the mortality risks related to inter-day and intra-day TVs varied by climate areas, seasons, and Köppen–Geiger climate types. This global study also recognized regions with higher mortality risks associated with inter-day and intra-day TVs.

For all-cause mortality, we observed an increase of 0.59 % and 0.22 % in mortality risk per IQR increase in intra-day TV_{0-7} and inter-day TV_{0-7}, respectively, which were consistent with previous studies (Guoet al., 2016; Yanget al., 2018; Zhanget al., 2019). The magnitude of our effect estimates for inter-day or intra-day TVs was lower than that of the total TV estimated in our previous study (Guoet al., 2016). Compared with another previous study using DTR as the indicator of intra-day temperature variation, we found a smaller mortality risk as well as a smaller attributable fraction related to the exposure of intra-day TV (Leeet al., 2018). The first reason is that we used the minimum intra-day TV of each location as the reference values to calculate the AF, while previous studies commonly used zero (assuming there is no temperature change) as the reference value. Another reason could be related to the inclusion of more communities and countries, and the differences in the lag period and structure. In the previous study, a longer lag period (up to 14 days) with a flexible lag structure was applied to DTR while we considered the impacts of intra-day TV to be the same across 0–7 lag days (Leeet al., 2018).

Our study provides new insights into the comparison of the health impacts of intra-day and inter-day temperature variations. Different from previous studies using DTR and TCN as indicators, we applied two novel indices, intra-day TV and inter-day TV, which enable us to directly compare the health impacts under the same framework (Huet al. 2021; Vicedo-Cabreraet al., 2016). Generally, we found that intra-day TV was associated with a higher mortality risk compared with inter-day TV. The results indicated that intra-day TV may explain the main part of the

Table 2
Attributable fractions (%) of both inter-day TV_{0-7} and intra-day TV_{0-7} in each country/region.

Country/region	All-cause mortality		Cardiovascular mortality		Respiratory mortality	
	Inter-day	Intra-day	Inter-day	Intra-day	Inter-day	Intra-day
Argentina	0.43 (0.35, 0.50)	1.65 (1.49, 1.81)	NA	NA	NA	NA
Australia	0.35 (0.29, 0.40)	1.43 (1.29, 1.57)	NA	NA	NA	NA
Brazil	0.26 (0.21, 0.30)	1.61 (1.45, 1.77)	0.50 (0.42, 0.58)	1.82 (1.56, 2.07)	0.35 (0.22, 0.47)	1.76 (1.32, 2.20)
Canada	0.51 (0.43, 0.60)	1.67 (1.51, 1.84)	0.96 (0.82, 1.11)	1.87 (1.61, 2.13)	0.68 (0.44, 0.92)	1.78 (1.34, 2.22)
Chile	0.21 (0.17, 0.25)	1.75 (1.58, 1.92)	NA	NA	NA	NA
China	0.32 (0.26, 0.37)	1.13 (1.02, 1.24)	0.61 (0.52, 0.71)	1.31 (1.13, 1.50)	0.40 (0.26, 0.54)	1.11 (0.84, 1.39)
Colombia	0.14 (0.12, 0.17)	1.21 (1.09, 1.33)	0.27 (0.23, 0.31)	1.35 (1.16, 1.54)	0.19 (0.12, 0.25)	1.31 (0.99, 1.64)
Costa Rica	0.12 (0.10, 0.14)	1.40 (1.26, 1.54)	0.22 (0.19, 0.25)	1.57 (1.35, 1.79)	0.16 (0.10, 0.21)	1.50 (1.12, 1.87)
Czech Republic	0.44 (0.37, 0.52)	1.25 (1.13, 1.37)	0.82 (0.70, 0.95)	1.39 (1.20, 1.59)	0.58 (0.37, 0.79)	1.33 (1.00, 1.66)
Ecuador	0.13 (0.11, 0.15)	1.19 (1.07, 1.31)	0.24 (0.20, 0.28)	1.27 (1.09, 1.45)	0.17 (0.11, 0.23)	1.30 (0.98, 1.63)
Estonia	0.39 (0.32, 0.46)	1.39 (1.25, 1.53)	0.74 (0.62, 0.85)	1.55 (1.33, 1.77)	0.52 (0.34, 0.71)	1.50 (1.13, 1.88)
Finland	0.40 (0.33, 0.47)	1.30 (1.17, 1.43)	0.75 (0.63, 0.86)	1.46 (1.26, 1.67)	0.55 (0.35, 0.74)	1.42 (1.06, 1.77)
France	0.34 (0.28, 0.40)	1.54 (1.39, 1.69)	NA	NA	0.45 (0.29, 0.61)	1.62 (1.22, 2.03)
French Caribbean	0.10 (0.08, 0.11)	1.15 (1.04, 1.27)	NA	NA	NA	NA
French Guiana	0.09 (0.07, 0.11)	1.45 (1.30, 1.59)	NA	NA	NA	NA
Réunion	0.10 (0.09, 0.12)	0.89 (0.80, 0.97)	NA	NA	NA	NA
Germany	0.39 (0.32, 0.45)	1.55 (1.40, 1.70)	NA	NA	NA	NA
Greece	0.31 (0.26, 0.36)	1.52 (1.37, 1.67)	0.58 (0.49, 0.67)	1.70 (1.46, 1.93)	0.40 (0.26, 0.54)	1.65 (1.24, 2.06)
Guatemala	0.14 (0.12, 0.17)	1.34 (1.21, 1.47)	NA	NA	NA	NA
Iran	0.38 (0.31, 0.44)	1.95 (1.76, 2.14)	0.70 (0.59, 0.81)	2.14 (1.84, 2.44)	0.50 (0.32, 0.68)	2.05 (1.54, 2.56)
Ireland	0.28 (0.23, 0.33)	1.16 (1.05, 1.28)	0.52 (0.44, 0.60)	1.29 (1.11, 1.48)	0.37 (0.24, 0.50)	1.25 (0.94, 1.56)
Israel	0.26 (0.21, 0.30)	1.41 (1.27, 1.55)	NA	NA	NA	NA
Italy	0.27 (0.22, 0.31)	1.56 (1.41, 1.71)	NA	NA	NA	NA
Japan	0.32 (0.26, 0.37)	1.34 (1.21, 1.48)	0.59 (0.50, 0.69)	1.51 (1.30, 1.72)	0.41 (0.26, 0.56)	1.45 (1.09, 1.81)
Kuwait	0.25 (0.21, 0.29)	1.14 (1.03, 1.25)	0.47 (0.40, 0.54)	1.28 (1.10, 1.46)	0.33 (0.21, 0.45)	1.21 (0.91, 1.52)
Mexico	0.23 (0.19, 0.27)	1.81 (1.63, 1.99)	0.43 (0.37, 0.50)	2.02 (1.74, 2.30)	0.30 (0.19, 0.41)	2.01 (1.51, 2.51)
Moldova	0.41 (0.34, 0.48)	1.70 (1.53, 1.87)	NA	NA	NA	NA
Netherland	0.35 (0.29, 0.41)	1.39 (1.25, 1.52)	NA	NA	NA	NA
Norway	0.40 (0.33, 0.46)	1.42 (1.28, 1.56)	0.74 (0.63, 0.86)	1.59 (1.37, 1.82)	0.54 (0.35, 0.73)	1.53 (1.15, 1.91)
Panama	0.15 (0.13, 0.18)	0.96 (0.87, 1.06)	0.29 (0.24, 0.33)	1.07 (0.92, 1.22)	0.19 (0.12, 0.26)	1.01 (0.76, 1.26)
Paraguay	0.54 (0.45, 0.63)	1.73 (1.56, 1.90)	1.02 (0.86, 1.17)	1.93 (1.66, 2.20)	0.72 (0.46, 0.98)	1.87 (1.40, 2.33)
Peru	0.12 (0.10, 0.14)	1.61 (1.45, 1.77)	NA	NA	NA	NA
Philippines	0.10 (0.09, 0.12)	0.82 (0.74, 0.90)	0.19 (0.16, 0.22)	0.92 (0.79, 1.05)	0.13 (0.09, 0.18)	0.88 (0.66, 1.10)
Portugal	0.30 (0.24, 0.35)	1.75 (1.58, 1.93)	0.55 (0.46, 0.63)	1.95 (1.67, 2.22)	0.39 (0.25, 0.52)	1.87 (1.41, 2.34)
Puerto Rico	0.11 (0.09, 0.12)	1.05 (0.95, 1.15)	NA	NA	NA	NA
Romania	0.42 (0.35, 0.49)	2.15 (1.94, 2.36)	NA	NA	NA	NA
South Africa	0.34 (0.28, 0.40)	2.24 (2.02, 2.47)	0.63 (0.53, 0.72)	2.53 (2.18, 2.89)	0.44 (0.28, 0.60)	2.53 (1.90, 3.15)
South Korea	0.37 (0.31, 0.44)	1.36 (1.22, 1.49)	0.70 (0.59, 0.81)	1.52 (1.30, 1.73)	0.49 (0.32, 0.67)	1.50 (1.13, 1.87)
Spain	0.27 (0.22, 0.31)	1.63 (1.47, 1.79)	0.50 (0.42, 0.57)	1.81 (1.55, 2.06)	0.35 (0.23, 0.48)	1.80 (1.35, 2.24)
Sweden	0.33 (0.27, 0.39)	1.29 (1.16, 1.42)	0.62 (0.52, 0.72)	1.44 (1.24, 1.64)	0.44 (0.28, 0.60)	1.38 (1.04, 1.73)
Switzerland	0.37 (0.31, 0.43)	1.41 (1.27, 1.55)	0.69 (0.58, 0.80)	1.57 (1.35, 1.79)	0.48 (0.31, 0.65)	1.50 (1.12, 1.87)
Taiwan	0.28 (0.23, 0.33)	1.26 (1.14, 1.39)	0.54 (0.46, 0.62)	1.43 (1.22, 1.63)	0.37 (0.24, 0.51)	1.40 (1.05, 1.74)
Thailand	0.16 (0.13, 0.19)	1.31 (1.18, 1.44)	0.30 (0.25, 0.34)	1.46 (1.26, 1.67)	0.21 (0.13, 0.28)	1.43 (1.07, 1.78)
UK	0.29 (0.24, 0.34)	1.15 (1.04, 1.27)	0.55 (0.46, 0.63)	1.28 (1.10, 1.46)	0.39 (0.25, 0.53)	1.22 (0.91, 1.52)
Uruguay	0.34 (0.28, 0.40)	1.33 (1.20, 1.46)	NA	NA	NA	NA
USA	0.43 (0.36, 0.51)	1.35 (1.22, 1.49)	0.81 (0.69, 0.94)	1.50 (1.29, 1.71)	0.57 (0.37, 0.78)	1.49 (1.12, 1.86)
Vietnam	0.13 (0.11, 0.16)	1.17 (1.06, 1.29)	0.26 (0.22, 0.30)	1.34 (1.15, 1.52)	0.17 (0.11, 0.23)	1.25 (0.94, 1.56)

(*continued on next page*)

Table 2 (*continued*)

Country/region	All-cause mortality		Cardiovascular mortality		Respiratory mortality	
	Inter-day	Intra-day	Inter-day	Intra-day	Inter-day	Intra-day
Pooled	0.35 (0.29, 0.41)	1.45 (1.31, 1.60)	0.66 (0.56, 0.76)	1.57 (1.35, 1.79)	0.44 (0.28, 0.60)	1.57 (1.18, 1.96)

Note. NA means data are unavailable in this country or region.

mortality risk related to temperature variation. There were positive associations between intra-day TV and mortality risk across all lag intervals while the associations between inter-day TV and all-cause mortality risk were negative with a shorter lag interval ($TV_{0–1}$ and $TV_{0–2}$). This may be reasonable because previous studies found that a negative TCN (temperature decrease between neighbouring days) presented a protective effect on mortality risk (Xiaoet al., 2021; Zhanet al., 2017). The potential mechanisms of this protective effect are still unclear, but may be related to factors such as causes of death, climate, geographic location, and demographics (Zhanet al., 2017). For example, unlike all-cause mortality, short-term inter-day TV exposure ($TV_{0–1}$ and $TV_{0–2}$) can significantly increase the risk of cardiovascular death. However, our results showed that inter-day TV elevated mortality risk with longer lag intervals, which indicated that inter-day temperature variation within a longer period would be more harmful. Previous studies have observed that longer durations of TV tend to have greater health impacts (Yanget al., 2018; Yanget al., 2021). For example, Yang et al reported that the non-accidental mortality risk increased by 0.60 % with every 1 °C increase in $TV_{0–7}$, while it was 0.35 % for $TV_{0–1}$ (Yanget al., 2018). This is also observed for specific causes, including cardiovascular and respiratory mortality (Yanget al., 2018). Our findings suggested that increasing trend of the mortality risk from total TV may be mainly contributed by the inter-day component.

The stratified analyses demonstrated that the effect estimates for mortality risks related to inter-day and intra-day TVs varied by climate areas, seasons, and Köppen–Geiger climate types. We have previously observed that people living in moderate areas were more vulnerable to

Table 3
Annual average attributable deaths of inter-day $TV_{0–7}$ and intra-day $TV_{0–7}$ in each country/region.

Country/region	All-cause mortality		Cardiovascular mortality		Respiratory mortality	
	Inter-day	Intra-day	Inter-day	Intra-day	Inter-day	Intra-day
Argentina	265 (220, 311)	1,029 (928, 1,131)	NA	NA	NA	NA
Australia	185 (153, 217)	764 (688, 839)	NA	NA	NA	NA
Brazil	464 (384, 544)	2,871 (2,587, 3,154)	281 (238, 324)	1,018 (875, 1,161)	73 (47, 99)	371 (279, 464)
Canada	640 (530, 750)	2,079 (1,874, 2,285)	407 (344, 469)	788 (678, 899)	72 (46, 97)	188 (141, 234)
Chile	93 (77, 109)	783 (706, 860)	NA	NA	NA	NA
China	766 (634, 898)	2,908 (2,621, 3,196)	592 (501, 683)	1,348 (1,158, 1,537)	126 (81, 171)	382 (287, 477)
Colombia	86 (71, 101)	726 (654, 798)	45 (38, 52)	227 (195, 259)	12 (7, 16)	82 (61, 102)
Costa Rica	2 (2, 2)	24 (22, 27)	1 (1, 1)	8 (7, 9)	0 (0, 0)	2 (2, 3)
Czech Republic	143 (118, 168)	405 (365, 445)	135 (114, 155)	228 (196, 260)	11 (7, 14)	24 (18, 30)
Ecuador	30 (24, 35)	267 (241, 294)	16 (13, 18)	84 (72, 95)	4 (3, 6)	34 (25, 42)
Estonia	30 (25, 35)	106 (96, 116)	29 (24, 33)	60 (52, 69)	1 (1, 2)	4 (3, 5)
Finland	29 (24, 34)	95 (86, 104)	20 (17, 24)	40 (34, 46)	3 (2, 3)	7 (5, 8)
France	373 (309, 438)	1,688 (1,521, 1,855)	NA	NA	31 (20, 42)	112 (84, 139)
French Caribbean	3 (2, 3)	33 (30, 37)	NA	NA	NA	NA
French Guiana	0 (0, 0)	6 (6, 7)	NA	NA	NA	NA
Réunion	1 (1, 1)	8 (7, 8)	NA	NA	NA	NA
Germany	521 (431, 611)	2,091 (1,884, 2,297)	NA	NA	NA	NA
Greece	89 (73, 104)	439 (395, 482)	79 (67, 91)	231 (198, 263)	12 (7, 16)	47 (36, 59)
Guatemala	11 (9, 13)	105 (95, 116)	NA	NA	NA	NA
Iran	232 (192, 272)	1,228 (1,107, 1,349)	187 (159, 216)	581 (500, 662)	22 (14, 30)	92 (69, 115)
Ireland	123 (102, 144)	514 (463, 565)	74 (62, 85)	184 (158, 209)	25 (16, 34)	85 (64, 107)
Israel	25 (21, 29)	137 (124, 151)	NA	NA	NA	NA
Italy	141 (117, 166)	786 (708, 863)	NA	NA	NA	NA
Japan	2,869 (2,374, 3,363)	12,185 (10,978, 13,389)	1,841 (1,558, 2,124)	4,686 (4,026, 5,343)	471 (302, 640)	1,660 (1,246, 2,073)
Kuwait	11 (9, 13)	50 (45, 54)	10 (8, 11)	26 (23, 30)	1 (1, 2)	4 (3, 5)
Mexico	398 (329, 466)	3,177 (2,863, 3,490)	195 (165, 226)	909 (782, 1,037)	50 (32, 68)	337 (253, 420)
Moldova	25 (21, 30)	104 (94, 114)	NA	NA	NA	NA
Netherland	72 (60, 84)	286 (258, 314)	NA	NA	NA	NA
Norway	21 (17, 25)	76 (68, 83)	15 (13, 17)	32 (27, 36)	3 (2, 4)	8 (6, 10)
Panama	4 (4, 5)	28 (25, 30)	3 (2, 3)	10 (9, 12)	0 (0, 1)	2 (2, 3)
Paraguay	16 (13, 19)	52 (47, 57)	10 (8, 11)	19 (16, 21)	2 (1, 3)	5 (4, 6)
Peru	109 (90, 128)	1,458 (1,314, 1,601)	NA	NA	NA	NA
Philippines	75 (62, 88)	582 (524, 640)	50 (43, 58)	235 (202, 268)	14 (9, 19)	90 (68, 113)
Portugal	146 (121, 171)	865 (780, 951)	101 (85, 117)	358 (308, 409)	18 (11, 24)	87 (65, 109)
Puerto Rico	3 (3, 4)	35 (31, 38)	NA	NA	NA	NA
Romania	173 (143, 202)	889 (801, 976)	NA	NA	NA	NA
South Africa	1,689 (1,398, 1,980)	11,236 (10,129, 12,341)	479 (405, 553)	1,938 (1,666, 2,208)	270 (173, 367)	1,557 (1,170, 1,941)
South Korea	518 (429, 607)	1,892 (1,705, 2,079)	223 (188, 257)	484 (416, 552)	50 (32, 68)	152 (114, 189)
Spain	324 (268, 380)	1,967 (1,773, 2,161)	208 (176, 239)	753 (647, 858)	48 (31, 66)	245 (184, 305)
Sweden	88 (73, 103)	343 (309, 377)	71 (60, 82)	166 (143, 189)	9 (6, 12)	28 (21, 35)
Switzerland	47 (39, 55)	181 (163, 199)	33 (28, 38)	75 (64, 85)	4 (3, 5)	13 (9, 16)
Taiwan	162 (134, 190)	728 (656, 800)	69 (59, 80)	183 (157, 209)	21 (13, 28)	77 (58, 97)
Thailand	294 (243, 344)	2,388 (2,152, 2,624)	100 (85, 116)	496 (426, 565)	47 (30, 63)	322 (242, 402)
UK	668 (553, 783)	2,635 (2,374, 2,896)	456 (386, 526)	1,073 (922, 1,224)	131 (84, 179)	410 (308, 512)
Uruguay	105 (87, 123)	408 (368, 449)	NA	NA	NA	NA
USA	5,015 (4,151, 5,878)	15,629 (14,082, 17,173)	3,347 (2,832, 3,860)	6,173 (5,305, 7,040)	603 (387, 819)	1,571 (1,179, 1,961)
Vietnam	35 (29, 41)	312 (281, 342)	15 (13, 18)	79 (68, 91)	4 (2, 5)	28 (21, 35)
Pooled	17,120 (14,170, 20,068)	76,598 (69,023, 84,160)	9,091 (7,692, 10,487)	22,492 (19,329, 25,645)	2,137 (1,369, 2,903)	8,027 (6,027, 10,017)

Note. NA means data are unavailable in this country or region.

long TV exposure (Guoet al., 2016). This could be explained by decomposing the total TV into intra-day and inter-day parts. For example, we found that mortality risks of inter-day TV in moderate cold or moderate warm areas increased substantially with the increment of the lag interval while the risks of intra-day TV remain stable, which may be the main driver of the elevated effects of long TV exposure in moderate areas. The season could be another important modification factor for the TV-mortality association. Consistent with previous studies, we observed that intra-day TV led to higher mortality risks in the cold and the moderate season compared with the warm season (Phosriet al., 2020; Qiuet al., 2013). By contrast, the mortality risks of inter-day TV in the warm season showed an upward trend with the increment of the lag interval, which even exceeded the effects of intra-day TV ($TV_{0–4}$ to $TV_{0–7}$). Affected mainly by local air mass advection due to anomalous atmospheric circulation, inter-day TV with lag intervals of 3–7 days could contribute to the occurrence of heatwaves and cold spells and thus may cause greater health hazards.(Guoet al., 2021) The TV effects also varied in different Köppen–Geiger climate areas. Our results showed that intra-day TV had higher acute effects ($TV_{0–1}$) in the tropical and dry climate, which was consistent with a previous study showing that people living in warmer and less humid regions were more vulnerable to high DTR(Zhanget al., 2018). This might stem from a combination of factors, including physiological, technological, and behavioural changes or adaptations in response to the climate (Leeet al., 2018). For instance, more water evaporation from the body could be observed in dry and hot environments, which would further restrict blood flow in the vascular system, potentially influencing disease susceptibility (Fanget al., 2023). These impacts could further heighten vulnerability to TV exposure.

Our results revealed that the TV-related mortality burden showed heterogeneity between regions and countries. For example, higher fractions of premature deaths attributable to intra-day TV were observed in Iran, Romania, and South Africa, which were twice as high as in countries with a lower burden. Similarly, we observed higher fractions of death attributable to inter-day TV in Paraguay and the USA. Generally, previous studies considering the health impacts of temperature variation were mainly conducted in East Asia, America, Europe, and Oceania (Chenget al., 2014; Guoet al., 2016; Leeet al., 2018). Our results, however, showed that attention should also be paid to regions like Africa and the Middle East. More importantly, research is urgently needed in low- and middle-income countries, where few comprehensive assessments on the health impacts of climate change have been completed (Costelloet al., 2009). It has been widely accepted that climate change would exacerbate health inequities between regions, countries, and communities (Romanelloet al., 2021). Thus, further research is required to tackle the health threat of temperature variation, including proposing a standardized monitoring and evaluation system with indicators for the health risks related to climate change, continuing training and capacity building in climate and health, and raising sufficient human and financial resources through government aid and fiscal policy (Costelloet al., 2009; Ebi and Otmani Del Barrio, 2017).

In this study, we quantified that 1.45 % and 0.35 % of all-cause death could be attributed to intra-day $TV_{0–7}$ and inter-day $TV_{0–7}$, respectively. While these values were lower than that reported for cold-related deaths (7.29 % in a prior study), they substantially exceeded the AF attributable to hot temperature (0.42 %) (Gasparriniet al., 2015). Currently, Heat-Health Warning Systems (HHWS) developed in many countries primarily rely on the mean temperature for reference value determination (Casanuevaet al., 2019). However, our estimations indicated that TV may lead to a comparable or even greater mortality burden compared to heat exposure. Notably, TV not only has a direct impact on health, but also interacts with ambient temperature, potentially amplifying its effect on mortality (Wu et al., 2022). Ignoring the effects of TV would underestimate the mortality burden attributable to extreme temperatures. Therefore, it is crucial to incorporate inter-day and intra-day TV into the existing early warning systems. By splitting TV into the inter-day and intra-day component within a unified framework, this study empowers policymakers to prioritize the metric with the greatest health impact according to the local climate, allowing for preventive measures and timely responses to mitigate adverse effects. For example, healthcare professionals can proactively identify vulnerable populations (e.g., children, the elderly, and those with underlying conditions) and collaborate with patients and their caregivers to implement primary and secondary prevention strategies (e.g., education, medication review/adjustment, and routine assessments) during periods of dramatical temperature fluctuation.

This study has some strengths. First, this is the first and largest global investigation of the health impacts of intra-day and inter-day TV. Using the MCC dataset from 758 communities of 47 countries or regions, our results could provide robust estimations and give a comprehensive evaluation on a global scale. Second, we applied a new method to decompose the TV into intra-day and inter-day parts based on the same framework, which enables us to compare the two indicators directly. However, several limitations should also be acknowledged. First, our study had insufficient coverage in less industrialized areas as only a few communities were included in regions like Africa and Central Asia. Thus, the current findings should be interpreted with caution. Secondly, exposure misclassification may be introduced as we used daily weather data at the community level. Third, we were unable to provide the gender- and age-specific associations due to the lack of demographic information. As a result, further investigations are needed to identify vulnerable populations in more countries. Furthermore, the inter-day and intra-day TV proposed in this study are incapable of capturing the direction of temperature change in a short period (typically within two days), while prior studies suggested that negative and positive TCN may exert differential mortality impacts (Xiaoet al., 2021; Zhanet al., 2017). Therefore, it is necessary to incorporate additional factors, such as season, climatic characteristics, and location, in the analysis of health impacts of inter-day TV.

In conclusion, the current multi-country time-series analysis provides evidence on the associations between the exposure to TV and daily all-cause, cardiovascular, and respiratory mortality. Our results indicated that intra-day TV may explain the main part of the mortality risk related to temperature variation while the mortality risks varied by lag interval, climate area, season, and climate type. The findings suggest that comprehensive evaluations should be proposed in more countries to help protect human health.

Data sharing

Data were collected within the MCC Collaborative Research Network under a data sharing agreement and cannot be made publicly available. Researchers can refer to MCC participants, who are listed as coauthors of this Article, for information on accessing the data for each country.

Ethical approval

Ethical approval was not required for our analysis of aggregate anonymized data from the MCC Collaborative Research Network database.

CRediT authorship contribution statement

Bo Wen: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Data curation, Conceptualization. **Yao Wu:** Writing – review & editing, Visualization, Validation, Conceptualization. **Yuming Guo:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Antonio Gasparrini:** Writing – review & editing, Data curation. **Shilu Tong:** Writing – review & editing, Data curation. **Ala Overcenco:** Writing – review & editing, Data curation. **Aleš Urban:** Writing – review & editing, Data curation. **Alexandra Schneider:** Writing – review & editing, Data curation. **Alireza Entezari:** Writing – review & editing, Data curation. **Ana Maria Vicedo-Cabrera:** Writing – review & editing, Data curation. **Antonella Zanobetti:** Writing – review & editing, Data curation. **Antonis Analitis:** Writing – review & editing, Data curation. **Ariana Zeka:** Writing – review & editing, Data curation. **Aurelio Tobias:**

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2024.108712.

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