Global, regional, and national burden of mortality associated with non-optimal ambient temperatures from 2000 to 2019: a three-stage modelling study

DOI:10.1016/S2542-5196(21)00081-4

The Lancet

Global, regional, and national burden of mortality associated with temperature variability from 2000 to 2019: a three-stage modelling study

--Manuscript Draft--

Manuscript Number:	THELANCET-D-21-08927
Article Type:	Article
Keywords:	Global burden; Mortality; Temperature variability
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Abstract:	Background Increased mortality risk is associated with temperature variability (TV). However, there is no comprehensive assessment of the TV-related mortality burden across the globe. Methods A three-stage meta-analytical approach was applied to assess the global TV-related mortality burden at a spatial resolution of 0·5° × 0·5° from 2000 to 2019. We firstly obtained location-specific TV-mortality associations based on daily time series of 750 locations from the Multi-country Multi-city Collaborative Research Network. Then, a multivariate meta-regression model was built with five predictors to estimate grid-specific TV-mortality associations. Finally, percentage excess in mortality and excess mortality rate were calculated to quantify the TV-related mortality burden and to further explore its temporal trend over two decades. Findings An increasing trend of TV was identified at the global level from 2000 to 2019. Globally, 1,490,596 deaths (95% confidence interval [CI]: 1,041,652, 1,945,553) were associated with TV per year, accounting for 3·3% (95% CI: 2·3, 4·3) of all deaths. Most of Asia, Northern Africa, Australia and New Zealand were observed to have higher percentage excess in mortality than the global average. Globally, the percentage excess in mortality increased about 1·1% (95% CI: 0·4, 1·7) per decade. Northern America, Sub-Saharan Africa, Australia and New Zealand, most of Asia, and Europe had a higher increasing rate in percentage excess in mortality than the global average, with the largest increase occurred in Australia and New Zealand (6·4%; 95% CI: 3·0, 9·6). Interpretation Globally, a substantial mortality burden was associated with TV, showing geographical heterogeneity and a slightly increasing temporal trend. Our results could contribute to the development of evidence-based intergovernmental strategies against the health consequences arising from TV. Funding Australian Research Council, Australian National Health & Medical Research Council.

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Global, regional, and national burden of mortality associated with temperature variability from 2000 to 2019: a three-stage modelling study

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Summary

Background

Increased mortality risk is associated with temperature variability (TV). However, there is no comprehensive assessment of the TV-related mortality burden across the globe.

Methods

A three-stage meta-analytical approach was applied to assess the global TV-related mortality burden at a spatial resolution of 0·5° × 0·5° from 2000 to 2019. We firstly obtained location-specific TV-mortality associations based on daily time series of 750 locations from the Multi-country Multi-city Collaborative Research Network. Then, a multivariate meta-regression model was built with five predictors to estimate grid-specific TV-mortality associations. Finally, percentage excess in mortality and excess mortality rate were calculated to quantify the TV-related mortality burden and to further explore its temporal trend over two decades.

Findings

An increasing trend of TV was identified at the global level from 2000 to 2019. Globally, 1,490,596 deaths (95% confidence interval [CI]: 1,041,652, 1,945,553) were associated with TV per year, accounting for 3·3% (95% CI: 2·3, 4·3) of all deaths. Most of Asia, Northern Africa, Australia and New Zealand were observed to have higher percentage excess in mortality than the global average. Globally, the percentage excess in mortality increased about 1·1% (95% CI: 0·4, 1·7) per decade. Northern America, Sub-Saharan Africa, Australia and New Zealand, most of Asia, and Europe had a higher increasing rate in percentage excess in mortality than the global average, with the largest increase occurred in Australia and New Zealand (6·4%; 95% CI: 3·0, 9·6).

Interpretation

Globally, a substantial mortality burden was associated with TV, showing geographical heterogeneity and a slightly increasing temporal trend. Our results could contribute to the development of evidence-based intergovernmental strategies against the health consequences arising from TV.

Funding

Australian Research Council, Australian National Health & Medical Research Council.

Research in context

Evidence before this study

In the past few years, attention has been increasingly paid to the negative health effects of short-term temperature variability (TV), an indicator of unstable weather that causes challenges to human adaption. We searched MEDLINE (via PubMed), Web of Science, and Google Scholar from database inception until Nov 6, 2021, for articles in English. We used a combination of search terms, including exposure terms ("temperature variability", "temperature change", "temperature fluctuation", "temperature range") and health outcome terms ("mortality", "mortality burden", "death", "excess death"). Although many studies have reported the association between TV and premature deaths, most evidence has been obtained from studies in single cities or countries, the systematic evaluation of the results is challenged by differences in modelling, parameterization, and publication bias. One study evaluated the mortality risk associated with TV based on data from 12 countries, but did not provide the attributable burden of TV-related mortality. The global burden of mortality associated with TV is still unknown.

Added value of this study

To the best of our knowledge, this is the largest and first study, using global gridded observation data at a spatial resolution of 0.5° × 0.5°, to systematically estimate the global burden of mortality associated with TV and explore its temporal trend over 20 years. This study identified an increasing trend of TV at the global level from 2000 to 2019. Globally, 1,490,596 deaths were associated with TV per year, accounting for 3.3% of all deaths. The percentage excess in mortality increased about 1.1% per decade from 2000 to 2019. Disparate geographical variations were also found.

Implications of all the available evidence

This study provides robust epidemiological evidence of the impact of TV on mortality globally, and across and within countries or regions. Our findings suggest that regions with a higher percentage excess in mortality due to TV (e.g., the whole of Asia, Australia and New Zealand, Northern Africa) are of great importance to contribute to coordinated actions for health, and more targeted policies should be implemented in regions with a higher increasing rate of TV-related mortality burden (e.g., Australia and New Zealand, Northern Europe and Western Europe).

Introduction

Climate change is a major public health concern in the 21st century. It affects both the global mean surface temperature and its variability, resulting in more frequent extreme weather events and unstable weather [1-3]. Globally, non-optimum temperatures have been identified as an important indicator of climate change given its largely recognized warming trend, and as one of the leading causes of the global burden of diseases [4-6]. However, temperature variability (TV), an indicator of short-term temperature fluctuations or stability which is also difficult for human beings to adapt to, is lack of public awareness and less investigated compared to non-optimum temperatures [7,8].

Some studies have reported the adverse health impacts of TV, showing a significant association between TV and mortality risk [9-12]. Our previous study based on Multi-Country Multi-City (MCC) Collaborative Research Network observed significant but varied associations between TV and mortality risk across 12 countries with various climate patterns, indicating that TV can affect the entire population but pose a higher risk to particular population groups [9]. Although several studies have investigated the association between TV and mortality [9-12], few so far have assessed the absolute mortality burden associated with TV.

We have seen an increased mortality burden attributable to hot temperatures [13], and it is also of great benefit to explore how TV-related mortality burden changes over time. Since the pre-industrial era, the global temperature has increased by more than 1 °C [14]. However, TV was observed to vary in time and space without consistent temporal patterns [15-17]. The reason for this temporal-spatial variation can be multifaceted. Dynamic temperature changes are highly correlated with long-wave radiation fluxes which depend on both natural (e.g., atmospheric circulation, cloud cover, and precipitation) and anthropogenic factors (e.g., overexploitation and excessive grazing) different from region to region [18-21]. All of these make it necessary to understand the temporal trend in TV-related mortality burden across the globe and make comparisons between regions at the same time window.

In this study, using data from the MCC Collaborative Research Network, we first explored the TV-mortality association across 43 countries/regions. Then, to provide a more comprehensive picture of the global burden of mortality associated with TV, global gridded temperature data with a resolution of $0{\cdot}5° \times 0{\cdot}5°$ were used to assess the TV-related mortality burden at the global, regional, and national levels. Furthermore, temporal trends in TV-related mortality burden were also explored from 2000 to 2019.

Method

Data sources

Location-specific mortality data

Daily death counts extracted from the MCC Collaborative Research Network database (http://mccstudy.lshtm.ac.uk/) were used in this study. A total of 750 cities across 43 countries/regions were included, accounting for 46·3% of the world's population. The International Classification of Diseases, 9th and 10th revision (ICD-9 and ICD-10) codes were used to identify causes of death. We extracted the data series on non-external causes of death (ICD-9: 0–799; ICD-10: A00–R99) or, if not available, all-cause mortality. The descriptive statistics by countries/regions are shown in Table S1. Only 0·09% of all-cause death data were missing (Table S2).

Gridded temperature data

Daily 1-hour maximum temperature (T_{max}) and minimum temperature (T_{min}) data at 0·5° × 0·5° latitude-longitude resolution during 1979–2019 were collected from the Climate Prediction Centre (CPC) Global Temperature data provided by the National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Laboratory (PSL) (https://www.psl.noaa.gov/data/gridded/data.cpc.globaltemp.html). The dataset is originated from The Global Telecommunication System (GTS) data covering T_{min} and T_{max} data from 6,000–7,000 stations across the globe and interpolated using the Shepard algorithm with consideration of orographic effects to develop gridded data [22]. The daily mean temperature was calculated by averaging the daily T_{min} and T_{max}. TV was calculated as the standard deviation (SD) of the daily T_{min} and T_{max} during several exposure days [9].

Gridded GDP and population data

Data on the global gross domestic product (GDP) and population in 0·5°-degree grid between 1980 and 2010 by 10 years were obtained from the Global Carbon Project [23]. GDP and population data were linearly interpolated over time to generate values for each year. GDP per capita was calculated by dividing the GDP by population. All GDP per capita data were adjusted to 2005 US dollars.

Gridded mortality data

We obtained country-specific mortality rate for 2010 from the World Bank, which was used to represent the average mortality rate for the period 2000 to 2019. The average daily deaths for each grid cell was computed as the product of grid-specific population and annual mortality rate of the country where the grid cell is located, divided by the number of days in a year. The mortality rates were assumed to be identical across all grid cells in the same country, which is widely used in the global burden diseases study [24-27].

Statistical analysis

Seasonal-trend decomposition

Using a seasonal-trend decomposition procedure based on locally weighted smoothing (STL), we decomposed time-series data of TV into seasonal, trend, and remainder components [28]. We applied the STL method to each grid cell to decompose the time-series data of TV and extract the long-term trend. The global trend of TV was then obtained by averaging long-term trends across all grid cells. The decomposed long-term trends were applied for descriptive purposes only.

TV-related mortality burden

A three-stage approach established and validated in our previous MCC studies was used to quantify the global TV-related mortality burden at a spatial resolution of $0{\cdot}5° \times 0{\cdot}5°$ [13,29]. To make our results easy to follow, we applied the length of exposure of 7 days in the main analyses, which showed the highest mortality burden in our preliminary analyses. Results for other lengths of exposure were shown in the sensitivity analyses.

In the first stage, a generalized linear regression with a quasi-Poisson family was applied to perform the analysis for each location, to obtain location-specific effect estimates for TV-mortality association. The equation was as follows [30]:

$$Y_{it} \sim Poisson(\mu; \theta)$$

$$\mathrm{E}(Y_{it}) = \exp(\alpha_i + \beta_i TV_{it} + cb(Temp_{it}, lag = 21) + ns(Time_{it}, df = 7/year) + \gamma_i DOW_{it})$$

$$VAR(Y_{it}) = \theta\mu$$

where Y_{it} denotes daily deaths count in location i on day t; α_i is the intercept in location i; β_i and γ_i represent the coefficients in location i; TV_{it} stands for the linear function of TV, which is commonly applied in previous studies [9]; $cb(Temp_{it}, lag = 21)$, built by distributed-lag nonlinear models (DLNMs), is a 2-dimensional cross-basis function of daily mean temperature featuring the nonlinear and delayed association over 21 days of lag, with a natural cubic spline function with three internal knots placed at the 25th, 50th, and 75th percentile of the location-specific temperature distribution and a natural cubic spline function with two internal knots placed at equally spaced values in the log scale, plus intercept; $\mathrm{n}s(Time_{it}, df = 7/year)$ is a natural cubic spline for time with 7 degrees of freedom (*df*) per year, which was applied to control for long-term trends and seasonality; and DOW_{it} stands for the day of the week coded as a categorical variable. $VAR(Y_{it})$ and μ denote the variance and expectation of Y_{it}, and θ is an overdispersion parameter. The association between TV and mortality was presented as the relative risk (RR) with 95% confidence interval (CI) associated with per 1 °C increase in TV. Percentage change in mortality with an interquartile increase in TV was also computed.

In the second stage, a multivariate meta-regression model was built to quantify the relationship between the location-specific effect estimates obtained from the first stage and a set of independent explanatory variables from each location. We identified five explanatory variables that were well documented in previous studies to contribute to the heterogeneity of location-specific effect estimates, including continents, five climate groups of Köppen climate classification, GDP per capita, the yearly average of daily mean temperature, and the range of daily mean temperature [13,31]. Mid-year GDP per capita (the middle year of the study period for each location) was calculated to reflect the average location-specific GDP per capita.

In the third stage, the fitted meta-regression model obtained in the second stage with five grid-specific explanatory variables was used to estimate the TV-mortality association between 2000 and 2019 at the grid cell level.

Then, we calculated the daily excess deaths associated with TV in each grid cell using the following equation:

$$RR_{it} = \exp(\beta_{per\ 1\ \text{°C}\ increase} \times TV_{it})$$

$$ED_{it} = (RR_{it} - 1) \times D_i$$

where RR_{it} is the RR of grid cell i on day t; $\beta_{per\ 1\ \text{°C}\ increase}$ is the grid-specific association; TV_{it} is the TV of grid cell i on day t; ED_{it} stands for the excess deaths in grid cell i on day t; D_i is the average number of daily deaths in grid cell.

The total number of excess deaths was computed as a sum of daily excess deaths for each year and the whole study period at the global, regional, and national levels. The percentage excess in mortality was calculated by the ratio of excess deaths to total deaths. The annual average percentage excess over 20 years was further computed. Annual excess deaths per 100,000 residents (excess death rate) were also presented. For each region or continent, we calculated the percentage change per decade in both percentage excess in mortality and excess death rate, using a linear regression model considering a Gaussian distribution of percentage excess and excess death rate on the log scale. The 95% CI of percentage change per decade was obtained based on 1,000 bootstrap replicates.

Sensitivity analysis

Several sensitivity analyses were performed to test the robustness of our results: (1) assessing different lengths of exposure to TV (from 0–1 to 0–6 days); (2) extending the maximum lag periods of mean temperature from 21 days to 24 and 28 days; and (3) using alternative *df* values for time trend (from 7 *df* per year to 6 *df* and 8 *df* per year) and lag days (from 4 *df* to 5 *df* and 6 *df*). In addition, as we used the counter-factual scenario of no variation in the main analyses, excess deaths represent those that would not have occurred if TV never exceeded 0 °C. Considering that TV is less likely to be zero, we also calculated the excess deaths under the counterfactual scenario of the grid-specific minimum TV, by excluding the excess deaths associated with TV ranging from zero to minimum value, to assess the mortality burden in the more stringent criteria.

R software (version 3·6·2) was used to perform all analyses. R package "dlnm" (version 2·4·2), "mixmeta" (version 1·0·8), and "stR" were used to perform DLNM model, meta-regression model, and seasonal-trend decomposition, respectively.

Results

Averaged over the last 20-year (2000 to 2019), the annual average TV is shown in Figure 1A. Globally, a large variation in TV was observed. Several regions were identified to have higher TV, such as North America, Southern Africa, and Northern Africa. For the time trend, the time series of daily global average TV is shown in Figure 1B, with the global average TV of 6·1 (±1·3) °C in 2000 and 6·3 (±1·3) °C in 2019 (Table S3). After seasonal-trend decomposition, a rising long-term trend in TV was found across the globe (Figure 1C and Figure S1). Among all regions, Australia and New Zealand had the largest increase in annual TV (Table S3).

Figure 2 shows a detailed overview of the TV-mortality risk and TV-related mortality burden across the globe. Generally, per interquartile increase in TV was associated with an average of 0·7% increases in mortality across all grid cells, with a median value of 0·6% (IQR: 0·3, 1·1). The geographical variation was observed globally, with South Asia had the highest mortality risk associated with TV (Figure 2A). Hotspot areas with the biggest contribution to the excess deaths were recognized in most parts of South and East Asia (Figure 2B). A higher percentage excess in mortality was observed in most of West Asia, the south of Middle Asia, and the north of South Asia (Figure 2C). The junction of Western Africa and Central Africa had the highest excess death rate (per 100,000 residents) (Figure 2D). The changing nature per decade of the percentage excess is shown in Figure 2E. The percentage excess in the southeast coast of Australia increased dramatically, along with separate areas in Western Asia. The excess death rates (per 100,000 residents) were shown to increase in the south of Southern Africa, Western Africa, southeast coast of Australia and Western Asia (Figure 2F).

From 2000 to 2019, globally, a total of 1,490,596 (95% CI: 1,041,652, 1,945,553) excess deaths was associated with TV per year (Table 1), accounting for 3·3% (95% CI: 2·3, 4·3) of the total deaths and 26 (95% CI: 18, 34) excess deaths per 100,000 residents (Figure 3 and Table S4). Three leading continents in terms of percentage excess in mortality were Asia (4·5%), Oceania (3·3%), and Americas (2·6%) (Figure 3A and Table S4). Southern Asia had the highest excess death rate (38; 95% CI: 29, 47 per 100,000 residents), with the lowest value observed for other regions in Oceania (11; 95% CI: -5, 27 per 100,000 residents) (Figure 3B and Table S4). In addition to the region, climate zones contributed to the variation in excess mortality (Table S5).

The global percentage excess in mortality increased from 3·2% (95% CI: 2·3, 4·2) to 3·3% (95% CI: 2·3, 4·3) between 2000 and 2019, representing an increased rate of 1·1% (95% CI: 0·4, 1·7) per decade

(Table 1). Australia and New Zealand generated the largest increase in percentage excess, increasing from 3·5% (95% CI: 1·5, 5·6) in 2000 to 4·4 (95% CI: 1·8, 7·0), representing an increased rate of 6·4% (95% CI: 3·0, 9·6) per decade. The largest decline occurred in other regions in Oceania, with a decreased rate of 8·5% per decade (Table 1).

Figure 4 shows the leading 20 countries ranked by TV-related mortality burden in both 2000 and 2019. The top 20 lists in two years included many of the same countries, while the order changed (Figure S2, Figure 4). Among the top 10 countries in percentage excess in 2019, 4 of them were listed in the current world bank high-income economies, including Saudi Arabia (1^{st}), United Arab Emirates (3^{rd}), Kuwait (4^{th}), and Qatar (7^{th}) (Figure 4A). Compared with the percentage excess, excess death rates (per 100,000 residents) changed slightly despite the changing order. (Figure 4B).

In the sensitivity analyses, the mortality burden associated with TV decreased with shorter exposure to TV and became minimal on TV 0–1 (Table S6–S7). After changing the model parameters, our results changed slightly (Table S8). When the counterfactual scenario of grid-specific minimum TV was applied, the percentage excess was 2·1% (95% CI: 1·5, 2·7), nearly two-thirds of that under the counterfactual scenario of zero TV (Table S9).

Discussion

To the best of our knowledge, this is the largest and first study to date, using global gridded observation data at a spatial resolution of 0·5° × 0·5°, to systematically estimate the global burden of mortality associated with TV and explore its temporal trend over 20 years. From 2000 to 2019, the daily average value of TV increased generally. A total of 1,490,596 deaths were associated with TV per year, accounting for 3·3% of all deaths. Globally, the percentage excess in mortality increased from 3·2% in 2000 to 3·3% in 2019, with an increased rate of 1·1% per decade. Geographical variations were observed in both TV-related mortality burden and its temporal changes.

Consistent with previous studies [11,12,32-34], we observed an increased mortality risk associated with TV, accounting for a substantial mortality burden. The percentage change in mortality associated with an interquartile increase in TV ranged from 0 to 2% for most of grid cells, which is comparable to our previous MCC study [9]. For example, our previous MCC study observed relatively higher mortality risk associated with TV for Australia, China, and Moldova, with their percentage change in mortality about 1% for per interquartile increase in TV; similar effect estimates were found by this study. The physiological mechanisms behind this association may relate to adaptation to temperatures or thermoregulation through physiological and behavioural responses, which are impeded by unstable weather [8,35]. During these processes, multiple organs can be involved (e.g., respiratory, circulatory, and immune systems) by affecting heart rate, blood viscosity, fibrinogen, platelet count, arterial blood pressure, and oxygen uptake [36-38]. Although the biological mechanisms have not been fully elucidated, they imply a hard process of adaption to TV.

To protect human health against TV, proactive counter-measures such as warning systems, community-level responses, and instructions for self-protection are necessary. Many policies have been developed to cope with the threatening of climate-related extreme events, for example, heat warning systems for heatwaves [39,40]. However, policies and strategies rarely exist to effectively cope with the adverse health impacts of TV. Our findings highlight the greater emphasis on the adverse effect of TV and the needs to develop early warning systems to reduce its health consequences. Besides, development of the guidance on self-protection and related social programs will be of great benefit to help people understand what they need to do. In the long run, measures to reduce the impact of climate change (e.g., clean energy and emission reduction) should be promoted to fundamentally solve or mitigate global warming as well as the increasing trend of TV, even though these measures may take time to implement and have an impact. Regions with a higher percentage excess in mortality due to TV (e.g., Asia, Australia and New Zealand, Northern Africa) are of great importance to contribute to coordinated actions for health. All should be aware that some countries, especially developing countries, will suffer disproportionately more from the adverse effects of global climate change, which could be a potential driver for international inequality [41].

In this study, we observed a small but significant increasing trend in both TV and TV-related mortality burden globally. Specifically, almost all regions showed an upward trend in mortality burden associated with TV, indicating persistent impact in the last two decades. Although few studies focused on the temporal trends of TV-related mortality burden, we can still explore clues through the relevant assessment of similar indicators. For example, a multi-country study included 20 countries/regions projected that a 1·4–10·3% increase in excess deaths attributable to the diurnal temperature range will happen by the end of this century, which inferred a more pronounced mortality burden due to unstable weather, although there may be an adaptation to climate change benefiting from socio-economic development and investment in public health [20,42,43]. More targeted policies should be implemented to avoid the negative health impacts of TV, especially for regions with a higher increasing rate of TV-related mortality burden (e.g., Australia and New Zealand, Northern Europe and Western Europe).

This study has several strengths. First, this is the first and largest study to systematically explore the mortality burden associated with TV on a global scale. Compared with previous studies restricted to a particular area [12,34,44], this study offers a finer spatial view of the mortality burden associated with TV, which can provide new clues on geographical variations and allow within country comparisons. Second, this study benefits from the global gridded population and climate data. To avoid potential exposure bias from aggregating individual exposure to location or country level, we used exposure data in 0·5°-degree grid, which produced better country-wide and global estimates. Finally, we simultaneously considered spatiotemporal trends over a 20-year period paralleled with fast climate change. Findings in this study provide a better understanding of how TV has affected human health amid inevitable warming trends and gradual acclimatization to climate change.

This study also has some limitations. In this study, grid-specific population data, GDP data, and mortality data in 2010 were used to represent average levels throughout the study period. By assuming these values unchanged, we were able to show the temporal trends of TV-related mortality burden associated with changes in TV [13]. However, this assumption could also make such estimates approximate. Meanwhile, we used country-specific mortality rates rather than grid-specific mortality rates due to a lack of data. While assuming identical mortality rates across grid cells within the same country is widely used in the global burden of disease study, it still limits our capability to identify variation in TV-related mortality burden within countries. Several predictors that could well explain the heterogeneity were used to estimate the grid-specific TV-mortality association. But we must acknowledge that there should be unexplained heterogeneity contributed from both the paucity of grid-specific data and indiscernible factors which limits the meta-analytic results. Further studies are warranted to provide more precise estimates of this association. Finally, MCC data have little information on countries in the Sahara Desert which experience high TV, and may affect the accuracy of effect estimates. Although we used Köppen climate classification as one of predictors in the model, future studies are needed to explore the association between TV and mortality in the desert area.

Conclusions

This study highlights the substantial mortality burden associated with TV. This burden had a complex pattern of variation globally and slightly increasing temporal trend over two decades. In light of climate change, our findings could assist in raising public awareness and improving the understanding of health impacts of TV. More coordinated action and greater accountability are needed to implement evidence-based intergovernmental strategies against the health consequences arising from unstable weather.

Contributors

YG, AG, MH, and BAr set up the collaborative network. YG, SL, YW, and QZ designed the study. YG, SL, QZ, and AG developed the statistical methods. YW, SL, and BW took the lead in drafting the manuscript and interpreting the results. YW, SL, QZ, BW, AG, ST, AO, AU, AS, AE, AMV-C, AZa, AA, AZe, AT, BN, BAl, BAr, BF, S-CP, CÍ, CAm, CDlCV, CÅs, DH, DVD, DR, EI, EL, FM, FA, FdD, SR, FS, GC-E, HKa, HO, HKi, I-HH, JK, JM, JS, JJKJ, KK, MHD, MSR, MH, MP, MdSZSC, NVO, NR, NS, PM, PMC, PG, PHNS, RA, SO, SF, TND, VC, VH, WL, XS, YH, YLG, MLB, and YG provided the data, and contributed to the interpretation of the results and the submitted version of the manuscript. YG, SL, YW, and QZ accessed and verified the data. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

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.

Declaration of interests

We declare no competing interests.

Acknowledgments

This study was supported by the Australian Research Council (DP210102076) and the Australian National Health and Medical Research Council (APP2000581). WY was supported by China

Scholarship Council (number 202006010044); SL by an Early Career Fellowship of the Australian National Health and Medical Research Council (number APP1109193); QZ by the Program of Qilu Young Scholars of Shandong University, Jinan, China; BW by China Scholarship Council (number 202006010043); JK and AU by the Czech Science Foundation (project number 20–28560S); NS by the National Institute of Environmental Health Sciences-funded HERCULES Center (P30ES019776); S-CP and YLG by the Ministry of Science and Technology (Taiwan; MOST 109–2621-M-002–021); YH by the Environment Research and Technology Development Fund (JPMEERF15S11412) of the Environmental Restoration and Conservation Agency; MdSZSC and PHNS by the São Paulo Research Foundation (FAPESP); ST by the Science and Technology Commission of Shanghai Municipality (grant number 18411951600); HO and EI by the Estonian Ministry of Education and Research (IUT34–17); JM by a fellowship of Fundação para a Ciência e a Tecnlogia (SFRH/BPD/115112/2016); AG and FS by the Medical Research Council UK (grant ID MR/R013349/1), the Natural Environment Research Council UK (grant ID NE/R009384/1), and the EU's Horizon 2020 project, Exhaustion (grant ID 820655); AS, SR, and FdD by the EU's Horizon 2020 project, Exhaustion (grant ID 820655); and VH by the Spanish Ministry of Economy, Industry and Competitiveness (grant ID PCIN-2017–046); YG by career development fellowships of the Australian National Health and Medical Research Council (number APP 1163693). This Article is published in memory of Simona Fratianni who helped to contribute the data for Romania.

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Tables

Table 1. Percentage excess in mortality and excess deaths per 100,000 residents in 2000 and 2019 and percentage change per decade over 2000–2019 by continent and region.

Region	Annual average excess deaths	Percentage excess in mortality (%)			Excess death, per 100,000 residents		
		2000	2019	Percentage change per decade (%)	2000	2019	Percentage change per decade (%)
Global	1,490,596 (1,041,652, 1,945,553)	3.2 (2.3, 4.2)	3.3 (2.3, 4.3)	1.1 (0.4, 1.7)	26 (18, 34)	26 (18, 34)	0.8 (0.1, 1.4)
Americas	133,705 (84,203, 183,993)	2.6 (1.6, 3.5)	2.6 (1.6, 3.5)	1.0 (-0.0, 2.2)	17 (11, 24)	17 (11, 24)	0.9 (-0.2, 2.1)
Northern America	71,256 (52,825, 89,869)	3.0 (2.2, 3.8)	3.0 (2.2, 3.7)	1.3 (0.1, 2.7)	24 (17, 30)	23 (17, 30)	1.2 (0.0, 2.5)
Latin America and the Caribbean	62,449 (31,378, 94,124)	2.2 (1.1, 3.4)	2.2 (1.1, 3.3)	0.7 (-0.4, 1.8)	13 (7, 20)	13 (7, 20)	0.5 (-0.6, 1.6)
Europe	106,299 (61,498, 151,476)	1.5 (0.9, 2.1)	1.6 (0.9, 2.3)	2.5 (0.7, 3.6)	17 (10, 25)	19 (11, 27)	2.1 (-0.1, 3.1)
Northern Europe	11,086 (7,579, 14,614)	1.4 (0.9, 1.8)	1.6 (1.1, 2.1)	3.1 (-0.2, 5.4)	13 (9, 17)	14 (10, 19)	2.1 (-0.9, 4.8)
Eastern Europe	47,849 (19,056, 76,910)	1.3 (0.5, 2.0)	1.3 (0.5, 2.2)	2.0 (0.3, 3.1)	18 (7, 29)	19 (8, 31)	1.8 (0.0, 2.8)
Western Europe	24,786 (18,271, 31,340)	1.6 (1.2, 2.1)	1.9 (1.4, 2.4)	3.6 (-1.7, 6.0)	16 (12, 20)	18 (13, 23)	3.5 (-0.9, 6.1)
Southern Europe	22,578 (16,591, 28,612)	2.2 (1.6, 2.8)	2.2 (1.6, 2.8)	1.9 (-0.5, 4.4)	21 (16, 27)	22 (16, 27)	1.3 (-0.9, 4.3)
Africa	147,757 (46,467, 250,418)	1.8 (0.5, 3.0)	1.8 (0.6, 3.0)	0.5 (-0.1, 1.1)	18 (6, 30)	18 (6, 30)	0.4 (-0.2, 1.0)
Northern Africa	40,764 (27,427, 54,270)	3.7 (2.5, 5.0)	3.6 (2.4, 4.7)	-2.6 (-3.7, -1.2)	23 (16, 31)	22 (15, 29)	-2.7 (-3.9, -1.2)
Sub-Saharan Africa	106,992 (19,040, 196,147)	1.5 (0.2, 2.7)	1.5 (0.3, 2.7)	1.6 (0.8, 2.5)	16 (3, 30)	17 (3, 30)	1.6 (0.9, 2.5)
Asia	1,096,560 (847,399, 1,349,098)	4.4 (3.4, 5.4)	4.5 (3.5, 5.5)	1.0 (0.0, 2.0)	31 (24, 38)	32 (24, 39)	0.8 (-0.2, 1.6)
South-eastern Asia	89,488 (59,748, 119,547)	2.9 (1.9, 3.8)	3.2 (2.2, 4.3)	2.6 (0.4, 4.8)	19 (13, 25)	21 (14, 28)	2.3 (0.2, 4.3)
Western Asia	50,915 (41,827, 60,114)	5.8 (4.8, 6.9)	5.9 (4.8, 6.9)	1.2 (-0.2, 3.4)	31 (25, 37)	31 (26, 37)	1.2 (-0.3, 3.4)
Central Asia	14,205 (10,618, 17,848)	5.1 (3.8, 6.4)	5.1 (3.8, 6.4)	0.2 (-1.0, 1.7)	32 (24, 41)	32 (24, 41)	0.2 (-0.9, 1.7)
Southern Asia	556,389 (421,244, 693,530)	5.2 (3.9, 6.5)	5.1 (3.9, 6.4)	0.1 (-1.5, 1.4)	38 (28, 47)	37 (28, 46)	0.1 (-1.5, 1.5)
Eastern Asia	385,563 (313,961, 458,058)	3.8 (3.1, 4.5)	4.1 (3.3, 4.9)	1.9 (0.1, 3.0)	28 (22, 33)	29 (24, 35)	1.3 (-0.3, 2.4)
Oceania	6,276 (2,086, 10,567)	3.1 (0.9, 5.4)	3.6 (1.2, 6.1)	4.5 (1.1, 8.0)	21 (6, 37)	25 (8, 41)	3.5 (0.4, 6.9)
Australia and New Zealand	5,641 (2,370, 8,992)	3.5 (1.5, 5.6)	4.4 (1.8, 7.0)	6.4 (3.0, 9.6)	23 (10, 36)	28 (12, 45)	5.2 (1.7, 8.2)
Other regions in Oceania	635 (-284, 1,575)	1.9 (-0.9, 4.8)	1.3 (-0.6, 3.3)	-8.5 (-22.3, 4.8)	16 (-7, 40)	11 (-5, 27)	-8.9 (-25.9, 4.2)

Figure legends

Figure 1. The annual average temperature variability at a spatial resolution of 0.5° × 0.5° (A), the time series of daily mean temperature variability (B), and its long-term trend after seasonal-trend decomposition (C) across the globe from 2000 to 2019.

Figure 2. Percentage change in mortality associated with an interquartile (for each grid cell) increase in temperature variability (A), Annual average excess deaths (B), percentage excess in mortality (C), excess deaths per 100,000 residents (D), change in percentage excess in mortality per decade (E), and change in excess deaths per 100,000 residents per decade (F) due to temperature variability in 2000–19 at a spatial resolution of 0.5° × 0.5°. The x-axis in (E) represent change in percentage points, not percentage change.

Figure 3. Annual average percentage excess in mortality (A) and excess deaths per 100,000 residents (B) due to temperature variability in 2000–19 by continent and region.

Figure 4. Leading 20 countries of percentage excess in mortality (A) and excess deaths per 100,000 residents (B) in 2000 and 2019.

Figure 1

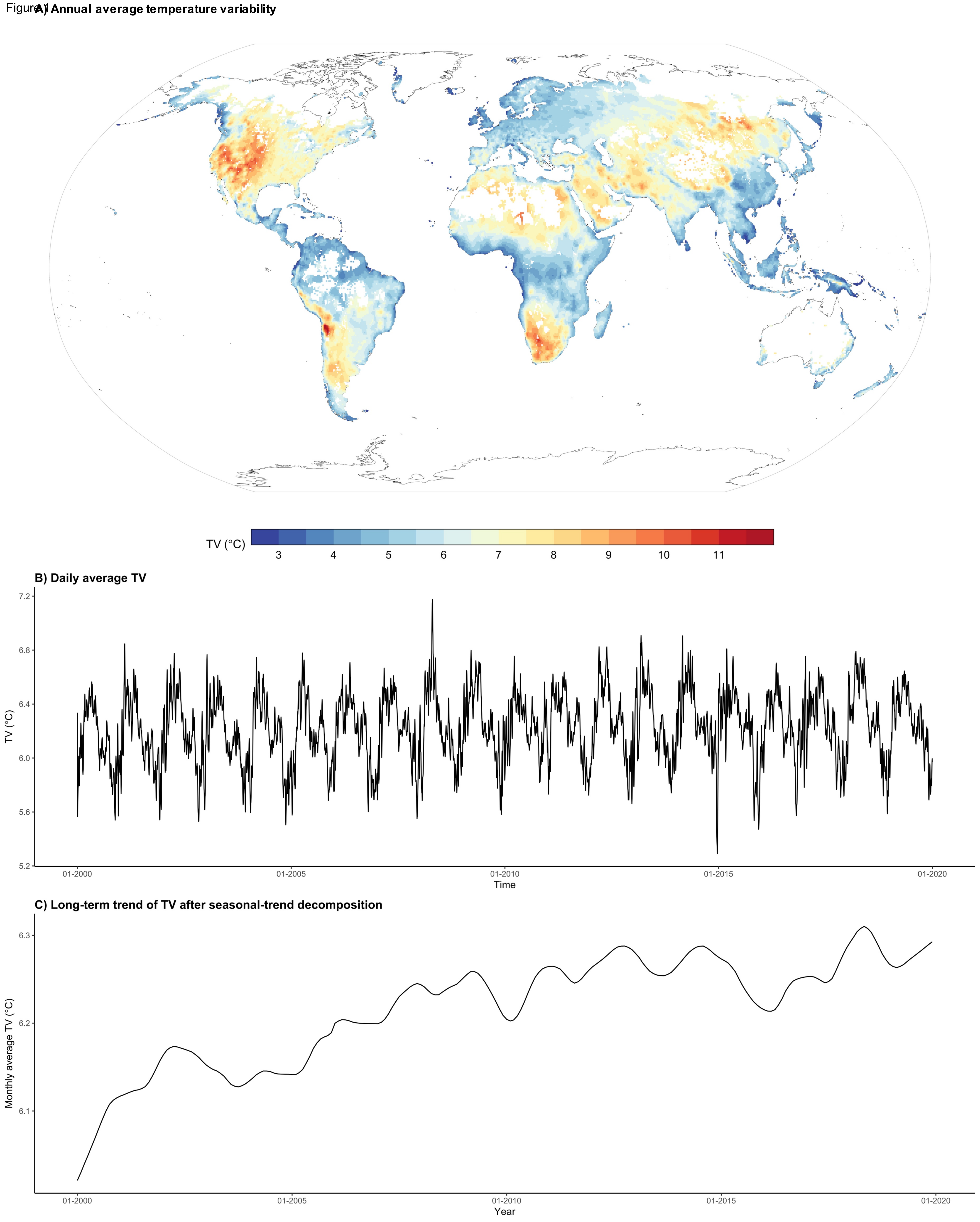
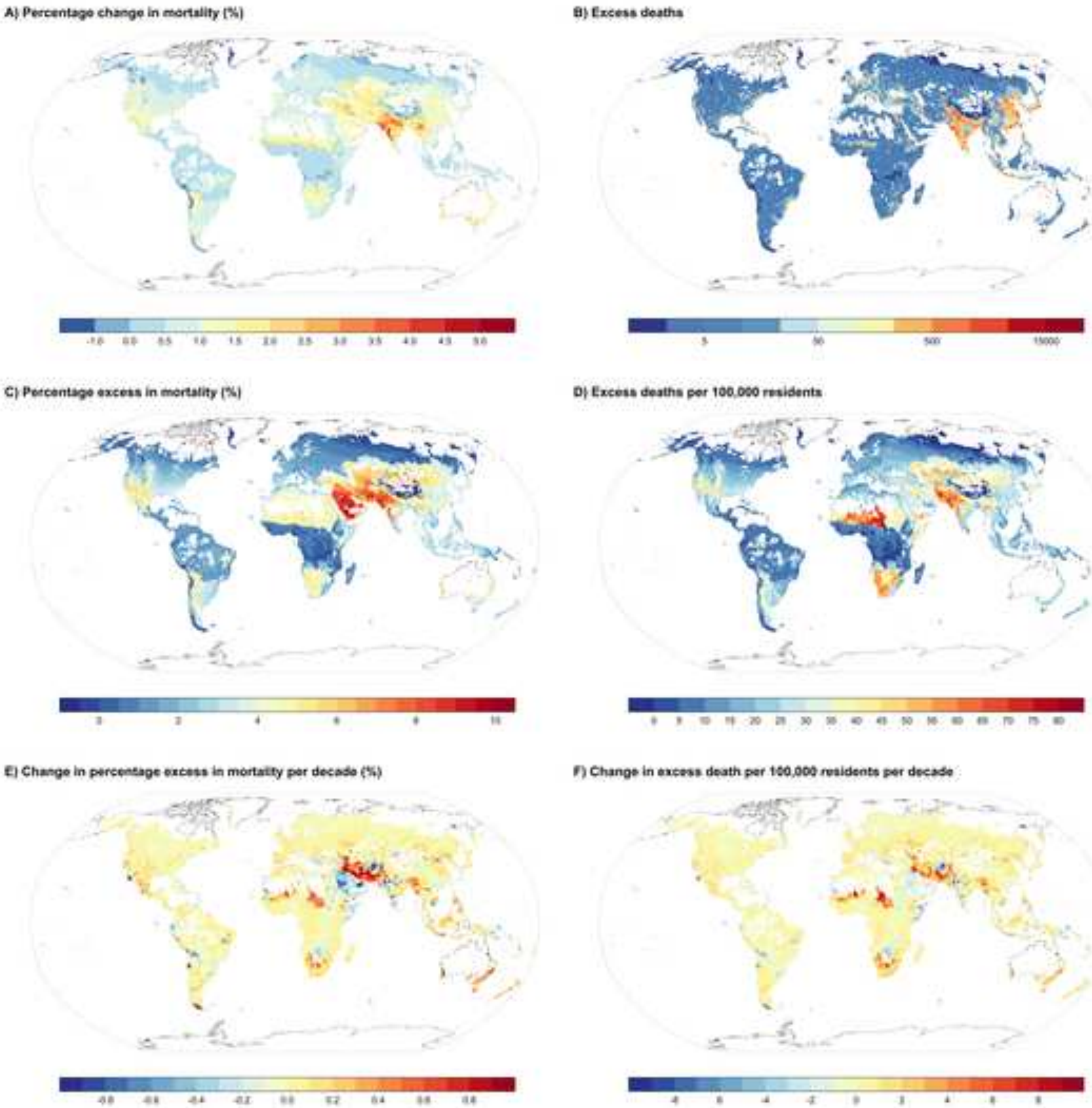

A) Annual average temperature variability
TV (°C)
3
4
5
6
7
8
9
10
11
B) Daily average TV
TV (°C)
7.2
6.8
6.4
6.0
5.6
5.2
01-2000
01-2005
01-2010
01-2015
01-2020
Time
C) Long-term trend of TV after seasonal-trend decomposition
Monthly average TV (°C)
6.3
6.2
6.1
01-2000
01-2005
01-2010
01-2015
01-2020
Year

Figure 2 Click here to access/download;Figure;Figure 2.jpeg



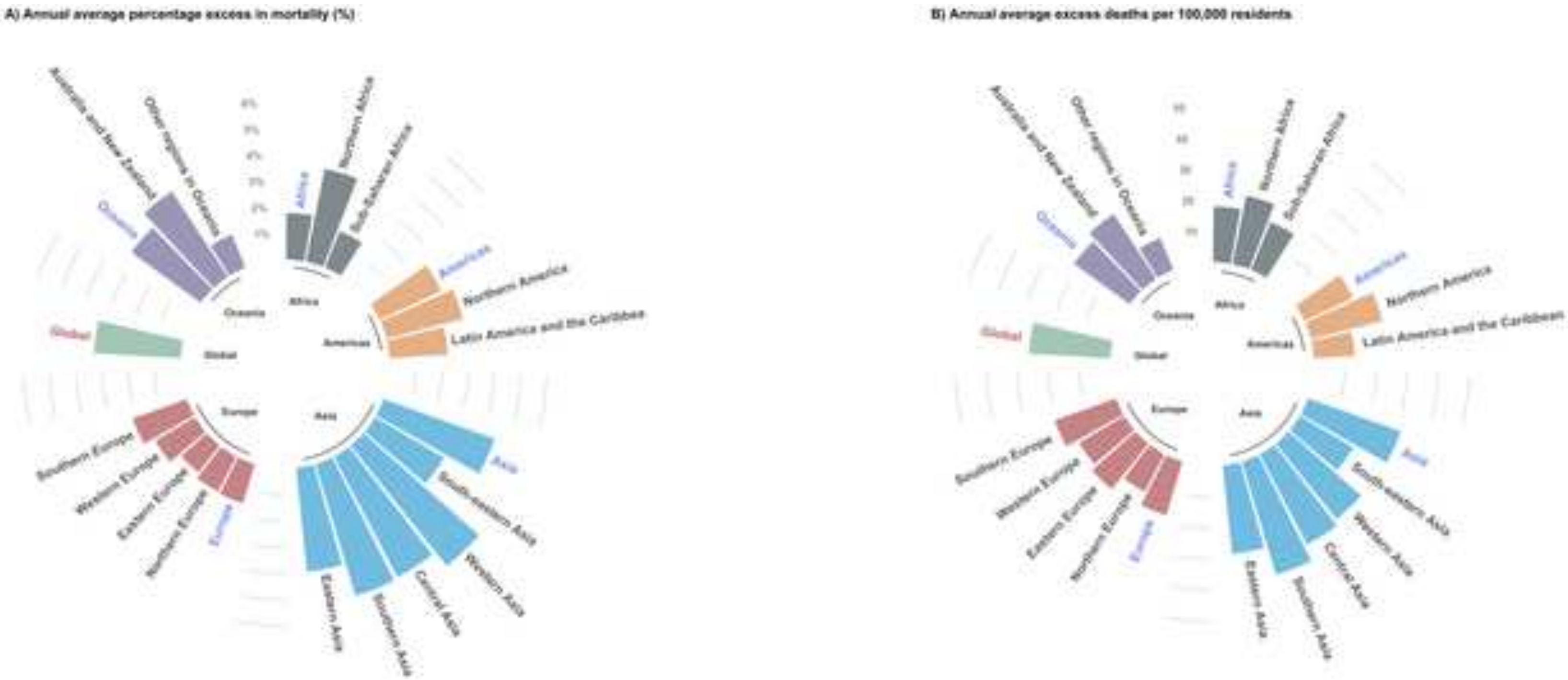

A) Annual average percentage excess in mortality (%)
B) Annual average excess deaths per 100,000 residents
Oceania
Australia and New Zealand
Other regions in Oceania
Africa
Northern Africa
Sub-Saharan Africa
Americas
Northern America
Latin America and the Caribbean
Global
Europe
Southern Europe
Western Europe
Eastern Europe
Northern Europe
Asia
South-eastern Asia
Western Asia
Central Asia
Southern Asia
Eastern Asia

Figure 4

A) Percentage excess in mortality (%)

Country	Percentage excess in 2000 (%)
1 United Arab Emirates	8.9 (7.2, 10.7)
2 Kuwait	8.8 (7.0, 10.6)
3 Saudi Arabia	8.8 (7.1, 10.5)
4 Jordan	7.4 (6.1, 8.7)
5 Qatar	7.1 (5.5, 8.6)
6 Oman	6.8 (5.6, 8.0)
7 Yemen, Rep.	6.6 (5.3, 7.9)
8 Iraq	6.6 (5.2, 8.0)
9 Syrian Arab Republic	6.5 (5.4, 7.6)
10 Turkmenistan	6.2 (4.8, 7.7)
11 Pakistan	6.0 (4.8, 7.3)
12 Uzbekistan	5.8 (4.5, 7.0)
13 Iran, Islamic Rep.	5.6 (4.5, 6.6)
14 Israel	5.5 (4.7, 6.3)
15 India	5.3 (4.0, 6.6)
16 Cyprus	5.3 (4.6, 5.9)
17 Tajikistan	5.2 (3.9, 6.4)
18 Afghanistan	5.1 (3.8, 6.4)
19 West Bank and Gaza	4.9 (4.3, 5.6)
20 Niger	4.9 (3.3, 6.5)
33 Azerbaijan	4.0 (3.3, 4.8)
34 Armenia	3.9 (3.1, 4.7)

Country	Percentage excess in 2019 (%)
1 Saudi Arabia	7.9 (6.3, 9.4)
2 Iraq	7.7 (6.0, 9.3)
3 United Arab Emirates	7.5 (6.0, 9.0)
4 Kuwait	7.5 (6.0, 9.0)
5 Jordan	7.4 (6.1, 8.6)
6 Pakistan	6.8 (5.4, 8.2)
7 Qatar	6.5 (5.1, 8.0)
8 Iran, Islamic Rep.	6.3 (5.1, 7.5)
9 Yemen, Rep.	6.1 (5.0, 7.3)
10 Syrian Arab Republic	6.1 (5.1, 7.2)
11 Turkmenistan	6.1 (4.7, 7.6)
12 Oman	5.8 (4.8, 6.9)
13 Cyprus	5.6 (4.9, 6.2)
14 Uzbekistan	5.5 (4.3, 6.7)
15 Israel	5.5 (4.7, 6.3)
16 West Bank and Gaza	5.1 (4.4, 5.8)
17 India	5.1 (3.8, 6.3)
18 Azerbaijan	5.0 (4.1, 5.9)
19 Tajikistan	4.9 (3.7, 6.1)
20 Armenia	4.9 (3.9, 5.9)
21 21 Niger	4.8 (3.3, 6.4)
30 Afghanistan	4.6 (3.5, 5.6)

B) Excess deaths per 100,000 residents

Country	Excess deaths per 100,000 residents in 2000
1 Niger	56 (38, 74)
2 Georgia	48 (40, 55)
3 Namibia	47 (33, 61)
4 Pakistan	46 (36, 55)
5 Eswatini	45 (31, 59)
6 Turkmenistan	45 (34, 55)
7 Chad	44 (16, 74)
8 Afghanistan	42 (31, 53)
9 Yemen, Rep.	41 (33, 49)
10 India	40 (30, 50)
11 Kazakhstan	39 (28, 51)
12 Somalia	39 (26, 53)
13 Sudan	39 (26, 52)
14 Armenia	38 (31, 46)
15 Botswana	38 (27, 49)
16 Burkina Faso	38 (23, 53)
17 Iraq	36 (29, 44)
18 Japan	36 (32, 41)
19 Cyprus	36 (31, 40)
20 Lesotho	36 (16, 55)
22 Myanmar	35 (24, 45)
23 Zimbabwe	34 (22, 45)
24 South Africa	33 (20, 46)

Country	Excess deaths per 100,000 residents in 2019
1 Georgia	56 (47, 65)
2 Eswatini	55 (38, 72)
3 Niger	55 (37, 72)
4 Namibia	51 (36, 67)
5 Pakistan	51 (41, 62)
6 Armenia	48 (38, 57)
7 Chad	45 (16, 75)
8 Turkmenistan	44 (34, 55)
9 Iraq	42 (33, 52)
10 Kazakhstan	42 (30, 54)
11 Botswana	41 (29, 53)
12 Lesotho	39 (18, 61)
13 Myanmar	39 (27, 51)
14 India	38 (29, 47)
15 Yemen, Rep.	38 (31, 45)
16 Zimbabwe	38 (25, 51)
17 South Africa	38 (23, 53)
18 Cyprus	38 (33, 42)
19 Afghanistan	37 (27, 46)
20 Japan	36 (32, 41)
21 Sudan	36 (24, 48)
23 Burkina Faso	36 (21, 50)
26 Somalia	31 (20, 41)