Socioeconomic inequality in vulnerability to all-cause and cause-specific hospitalisation associated with temperature variability: a time-series study in 1814 Brazilian cities

Rongbin Xu, Qi Zhao, Micheline S Z S Coelho, Paulo H N Saldiva, Michael J Abramson, Shanshan Li, Yuming Guo

Summary

Background Exposure to temperature variability has been associated with increased risk of mortality and morbidity. We aimed to evaluate whether the association between short-term temperature variability and hospitalisation was affected by local socioeconomic level in Brazil.

Methods In this time-series study, we collected city-level socioeconomic data, and daily hospitalisation and weather data from 1814 Brazilian cities between Jan 1, 2000, and Dec 31, 2015. All-cause and cause-specific hospitalisation data was from the Hospital Information System of the Unified Health System in Brazil. City-specific daily minimum and maximum temperatures came from a 0·25°×0·25° Brazilian meteorological dataset. We represented city-specific socioeconomic level using literacy rate, urbanisation rate, average monthly household income per capita (using the 2000 and 2010 Brazilian census), and GDP per capita (using statistics from the Brazilian Institute of Geography and Statistics for 2000–15), and cities were categorised according to the 2015 World Bank standard. We used quasi-Poisson regression to do time-series analyses and obtain city-specific associations between temperature variability and hospitalisation. We pooled city-specific estimates according to different socioeconomic quartiles or levels using random-effect meta-analyses. Meta-regressions adjusting for demographic and climatic characteristics were used to evaluate the modification effect of city-level socioeconomic indicators on the association between temperature variability and hospitalisation.

Findings We included a total of 147 959 243 hospitalisations (59·0% female) during the study period. Overall, we estimated that the hospitalisation risk due to every 1°C increase in the temperature variability in the current and previous day (TV_{0-1}) increased by 0·52% (95% CI 0·50–0·55). For lower-middle-income cities, this risk was 0·63% (95% CI 0·58–0·69), for upper-middle-income cities it was 0·50% (0·47–0·53), and for high-income cities it was 0·39% (0·33–0·46). The socioeconomic inequality in vulnerability to TV_{0-1} was especially evident for people aged 0–19 years (effect estimate 1·21% [1·11–1·31] for lower-middle income *vs* 0·52% [0·41–0·63] for high income) and people aged 60 years or older (0·60% [0·50–0·70] *vs* 0·43% [0·31–0·56]), and for hospitalisation due to infectious diseases (1·62% [1·46–1·78] *vs* 0·56% [0·30–0·82]), respiratory diseases (1·32% [1·20–1·44] *vs* 0·55% [0·37–0·74]), and endocrine diseases (1·21% [0·99–1·43] *vs* 0·32% [0·02–0·62]).

Interpretation People living in less developed cities in Brazil were more vulnerable to hospitalisation related to temperature variability. This disparity could exacerbate existing health and socioeconomic inequalities in Brazil, and it suggests that more attention should be paid to less developed areas to mitigate the adverse health effects of short-term temperature fluctuations.

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For the Portugese translation of the abstract see Online for appendix 1

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Introduction

Ambient temperature is an important determinant of environmental health.[1] Although most studies have focused on the health effects of low and high temperatures,[1] attention has been increasingly paid to mortality and morbidity related to short-term temperature fluctuation or temperature variability.[2–4] At the population level, the negative health effects of adverse temperatures are not evenly distributed. For instance, people living in low-income and middle-income countries and those with lower socioeconomic status tend to be more susceptible to heat-related mortality than those in high-income countries or higher socioeconomic status.[5,6] However, whether there is a similar socioeconomic inequality in the vulnerability to temperature variability remains largely unknown.

Current studies addressing this question have shown controversial findings. Hu and collegues[7] found that rural residents in 89 counties in Zhejiang province, China, were more susceptible to mortality related to temperature variability than urban residents were. By contrast, Zhang and colleagues[8] reported opposite results in 12 counties in Hebei province, China. Yang and

Research in context

Evidence before this study

We searched MEDLINE, Web of Science, and Google Scholar using "temperature variability" and terms of health outcomes ("health", "mortality", "morbidity", "hospitalization", "hospitalisation", "outpatient", "emergency department visit", "general medical consultations") on Oct 4, 2019, from inception, for articles in English. We included original and review articles that evaluated the effect of short-term temperature variability on mortality or morbidity. We found that many studies had suggested that high temperature variability within several days could significantly increase mortality or morbidity. However, studies on whether socioeconomic factors affect people's vulnerability to short-term temperature variability show mixed findings. Most studies only focused on mortality. Some found that residents living in rural areas or with low educational level were more susceptible to temperature variability-related mortality than urban and well-educated residents. By contrast, a study in 12 counties in China reported opposite results. A large study in 184 Chinese cities found that city-specific associations between temperature variability and hospitalisation were not significantly modified by local gross domestic product per capita. However, this study evaluated hospitalisations from cardiovascular diseases only; little is known about the socioeconomic inequality in vulnerability to other cause-specific outcomes. The relatively low number of locations in existing studies could give insufficient statistical power to detect inter-city socioeconomic disparities in human vulnerability to short-term temperature variability, and evidence beyond China and the USA is needed.

Added value of this study

To our knowledge, this is by far the largest and most comprehensive study to evaluate socioeconomic inequality in human vulnerability to short-term temperature variability. We included almost 148 million hospitalisations from 1814 cities, covering nearly 80% of the Brazilian population over 16 years and evaluating both all-cause and cause-specific hospitalisations. Our study found that people living in less developed cities in Brazil were more vulnerable to temperature variability-related hospitalisations. This socioeconomic disparity was especially evident for young (aged 0–19 years) and older (aged ≥60 years) people, and for hospitalisations due to infectious, respiratory, and endocrine diseases. This disparity might exacerbate the existing health and socioeconomic inequality in Brazil. Our results might also provide an important reference for other middle-income and high-income countries, given the large diversity in socioeconomic levels of the cities included.

Implications of all the available evidence

People living in less developed areas tend to be more vulnerable to temperature variability-related hospitalisations. Therefore, short-term temperature fluctuations might be a potential threat to health equity. More attention should be paid to areas with low socioeconomic levels to mitigate the adverse health effects of short-term temperature fluctuations.

colleagues[9] suggested that the association between temperature variability and mortality was only significant among those with primary or lower education, but not those with secondary or higher education. Interestingly, they did not find a significant modification effect of the local illiteracy rate on the city-specific association between temperature variability and mortality in 31 major Chinese cities.[9] However, these studies all focused only on the association between temperature variability and mortality. Studies related to socioeconomic inequality in the association of morbidity (eg, hospitalisation or emergency department visit) with temperature variability are even scarcer. A large study[2] in 184 Chinese cities found that the city-specific association between temperature variability and hospitalisation was not significantly modified by local gross domestic product (GDP) per capita. However, this study only included hospitalisations due to cardiovascular diseases.

The low number of locations (up to 184 cities) in these studies could have an insufficient statistical power to detect inter-city socioeconomic disparities in the vulnerability to short-term temperature variability. Apart from all-cause mortality and cardiovascular mortality and morbidity, little is known about the socioeconomic inequality in vulnerability to other cause-specific outcomes. Furthermore, studies from other countries are needed, given that the previous studies were mainly done in China and the USA.

In our previous studies,[10–12] we have found significant associations between temperature variability and hospitalisation associations across sex, age groups, specific causes, and geographical regions in Brazil during 2000–15. We found that about 3·5% of hospitalisations were attributable to short-term temperature variability, and that the association between temperature variability and hospitalisation varied by region, with the greatest effect size observed in the central western region and the lowest in the southern region.[10] However, whether the geographical variation in the association could be explained by city-level socioeconomic status is yet to be tested. This is an important research question for Brazil, where there is large socioeconomic and health inequality between different regions.[13,14] This study aimed to evaluate whether the association between temperature variability and overall and cause-specific hospitalisation could be modified by local socioeconomic level in 1814 Brazilian cities during 2000–15.

Methods

Study setting and dataset

The data collection for this time-series study has been described in detail in our previous publications.[10,13,15–17]

Briefly, all-cause and cause-specific hospitalisation data for 5570 Brazilian cities between Jan 1, 2000, and Dec 31, 2015, were extracted from the Hospital Information System (SIH) of the Unified Health System (SUS) through applying a data request to the Brazilian Ministry of Health. The SIH–SUS stores information on hospitalisations financed by SUS in either public or privately contracted hospitals, which account for about 70–80% of hospitalisations in Brazil.[18,19] Hospitalisations through the private health system (ie, not financed by SUS) were not included in this database. The SIH–SUS is designed mainly for the purpose of financial reimbursement to health service providers, and hospitalisation data are sent through a virtual hospitalisation authorisation form following the same standardised procedure in all cities across the country.[18,19] We included data from 1814 cities, whose electronic medical records were completed during the study period, in order to minimise the impacts of missing data. These 1814 cities are located in five regions (in the north, northeast, central west, southeast, and south) and cover 78·4% of the Brazilian population. The hospitalisation dataset recorded sex, age, and date of each admission. We divided the all-cause hospitalisation into 11 main cause categories according to the 10th revision of the International Classification of Diseases (ICD-10; appendix 2 p 2). City-specific daily minimum and maximum temperatures came from a 0·25°×0·25° Brazilian meteorological dataset.[20] This dataset only covered 1980–2013 when it was first published, but Xavier and colleagues[20] have since updated it to cover 1980–2017 using the same methods as the original.[20] Daily mean temperature was approximated as the average of daily minimum and maximum temperature.

See Online for appendix 2

We used four available city-level indicators to represent city-specific socioeconomic level: literacy rate of people aged 15 years or older; urbanisation rate (ie, the proportion of the population living in urban areas); average monthly household income per capita; and GDP per capita. We obtained city-specific literacy rates

	Region					National
	North	Northeast	Central west	Southeast	South	
Number of cities	28	662	128	622	374	1814
Number of hospitalisations	3 904 208	42 875 430	11 997 508	63 859 654	25 322 443	147 959 243
Female	2 484 050 (63·6%)	26 838 411 (62·6%)	7 113 235 (59·3%)	36 582 429 (57·3%)	14 341 510 (56·6%)	87 359 664 (59·0%)
Male	1 420 158 (36·4%)	16 037 019 (37·4%)	4 884 273 (40·7%)	27 277 225 (42·7%)	10 980 933 (43·4%)	60 599 579 (41·0%)
Age, years						
0–19	1 350 354 (34·6%)	12 966 669 (30·2%)	3 301 628 (27·5%)	14 630 251 (22·9%)	6 010 575 (23·7%)	38 271 100 (25·9%)
20–39	1 551 607 (39·7%)	15 534 906 (36·2%)	4 223 392 (35·2%)	20 700 262 (32·4%)	7 563 646 (29·9%)	49 582 228 (33·5%)
40–59	545 615 (14·0%)	7 304 040 (17·0%)	2 408 159 (20·1%)	14 698 498 (23·0%)	5 919 142 (23·4%)	30 865 587 (20·9%)
≥60	456 633 (11·7%)	7 069 815 (16·5%)	2 064 330 (17·2%)	13 830 642 (21·7%)	5 829 079 (23·0%)	29 240 329 (19·8%)
Literacy rate of people aged ≥15 years, %	88·1% (83·8–90·8)	72·9% (68·2–78·0)	89·0% (87·3–91·1)	92·5% (90·0–94·3)	93·5% (90·7–95·5)	89·1% (75·5–93·3)
Urbanisation rate, %	70·5% (62·7–86·7)	60·6% (47·7–75·8)	84·9% (78·1–91·6)	89·7% (78·7–95·9)	83·7% (70·5–92·0)	80·8% (60·7–91·5)
Average monthly household income per capita, US$	183 (143–250)	112 (98–135)	245 (218–273)	258 (216–298)	271 (232–318)	217 (123–275)
GDP per capita, $	4077 (3063–5309)	1982 (1594–2748)	5551 (3880–7518)	5739 (4028–8034)	6602 (4989–8709)	4406 (2205–6878)
Proportion of population aged 0–19 years, %	39·9% (36·2–46·8)	37·7% (35·6–40·3)	33·6% (31·8–36·3)	30·6% (28·7–32·9)	31·0% (29·2–33·4)	33·4% (30·2–37·5)
Proportion of population aged ≥60 years, %	6·9% (6·3–7·7)	10·7% (9·3–12·3)	9·4% (7·7–11·3)	12·5% (10·7–14·0)	12·1% (10·3–13·9)	11·5% (9·7–13·3)
Daily mean temperature, °C	27·2 (26·2–28·0)	26·3 (24·5–27·6)	25·4 (23·4–26·9)	22·7 (20·1–24·8)	20·8 (17·2–23·6)	24·2 (21·3–26·4)
TV_{0-1}	5·6 (4·8–6·7)	5·6 (4·6–6·7)	6·9 (5·8–8·2)	6·6 (5·4–7·8)	6·1 (5·0–7·2)	6·1 (5·0–7·3)

Data are n, n (%), or median (IQR). Household income and GDP per capita and were adjusted to 2015 prices. The literacy rate, urbanisation rate, and GDP per capita were the 16-year average values for 2000–15. Household income came from the 2010 Brazilian census. GDP=gross domestic product. TV_{0-1}=temperature variability exposure for the current and previous day.

Table: **Hospitalisations and socioeconomic, demographic, and climatic characteristics of 1814 Brazilian cities in 2000–15**

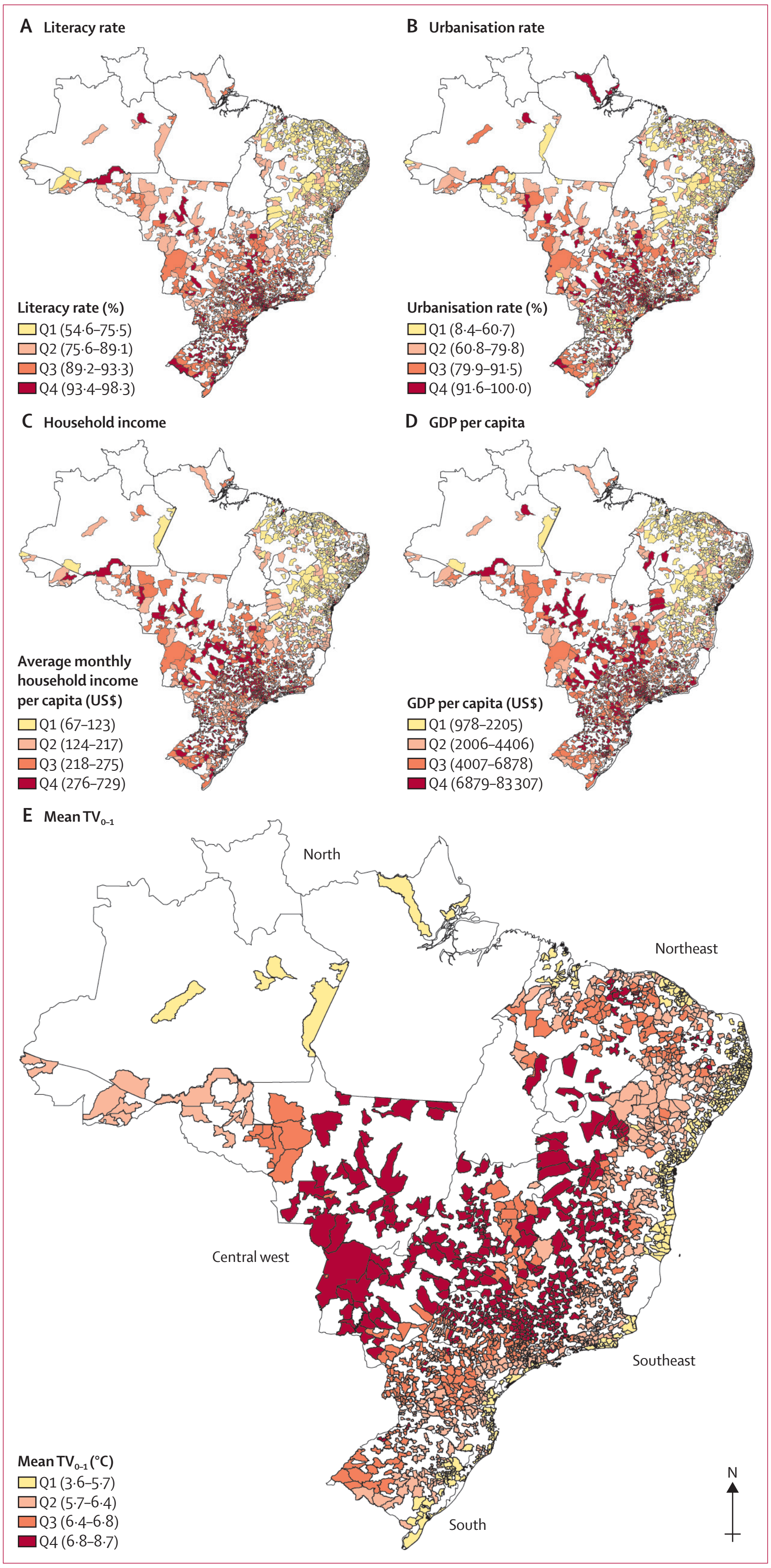

Figure 1: **City-level socioeconomic characterises and mean TV_{0-1} of 1814 Brazilian cities during 2000–15**
Household income and GDP per capita were adjusted to 2015 prices. The literacy rate, urbanisation rate, and GDP per capita were the 16-year average values during 2000–15. Household income came from the 2010 Brazilian census. Q1–Q4=lowest to highest quartiles of each city-level indicator. TV_{0-1}=temperature variability exposure for the current and previous day. GDP=gross domestic product.

and urbanisation rates from the 2000 and 2010 Brazilian census,[21] and we filled the data gap in other years using linear interpolation. City-specific household income data was only available from the 2010 Brazilian census. The city-specific average GDP per capita during 2000–15 came from official statistics released by the Brazilian Institute of Geography and Statistics (BIGS). All GDP per capita and household income data were adjusted to 2015 prices according to the consumer price index. We then further adjusted the GDP per capita and household income to US dollars according to the average exchange rate in 2015. The consumer price index and exchange rate data also came from BIGS. The 16-year average of literacy rate, urbanisation rate, and GDP per capita during 2000–15, and the household income in 2010 were used in our final analyses. From the 2010 Brazilian census, we also collected the proportion of the young population (0–19 years) and older population (≥60 years) as an indicator of population age structure. We downloaded all these socioeconomic and demographic data from the BIGS official website (appendix 2 pp 2–4). The 1814 cities were classified into four groups (Q1–Q4) according to the quartiles of each socioeconomic indicator. We also classified the cities as lower-middle income (GDP per capita of US$1146–4035), upper-middle income ($4036–12 475) and high-income (>$12 475) according to the 2015 World Bank standard.[22] There is only one city with a GDP per capita of less than $1146 ($978), which we classified as lower-middle income.

This study was approved and exempted by the Monash University Human Research Ethics Committee. The Brazilian Ministry of Health did not require ethical approval or informed consent for secondary analysis of aggregate anonymised data from the Brazilian Hospital Information System. Patient consent was not required for secondary analyses of anonymous data from the Brazilian Hospital Information System.

Statistical analysis

Short-term temperature variability was defined as the SD of daily maximum (T_{max}) and minimum (T_{min}) temperatures during several exposure days. Temperature variability exposure for the current and previous day (TV_{0-1}) was calculated as the SD (T_{min_lag0}, T_{max_lag0}, T_{min_lag1}, T_{max_lag1}). Temperature variability exposure for the current day and the previous two days (TV_{0-2}) was calculated as the SD (T_{min_lag0}, T_{max_lag0}, T_{min_lag1}, T_{max_lag1}, T_{min_lag2}, T_{max_lag2}), with the same pattern for TV_{0-3} to TV_{0-7}. TV_{0-1} to TV_{0-7}

are contributed to by both intra-day and inter-day temperature fluctuations during the exposure days.[4] Therefore, our temperature variability indicators tend to be comprehensive measurements of short-term temperature fluctuations across several days.

We used a two-stage time-series design to quantify the associations between temperature variability and risk of hospitalisation. The first stage has been described in detail in our previous paper.[10] Briefly, a quasi-Poisson regression was used to estimate the city-specific association between temperature variability and hospitalisation on the basis of the time-series data. The dependent variable was the city-specific daily hospitalisation counts with quasi-Poisson distribution. We added temperature variability to the model using a linear function according to our preliminary analyses.[10] The model adjusted for the potential non-linear effects of daily mean temperature by adding a cross-basis function with up to 21 lag days for daily mean temperature, using a natural cubic spline with 4 degrees of freedom for both temperature and lag days.[4,10] Long-term trends and seasonality were adjusted by adding a natural cubic spline for date with 7 degrees of freedom per year.[4,10] The model also adjusted for day of the week and public holidays. The association between temperature variability and hospitalisation was reported as the percentage increase in the risk of hospitalisation (with 95% CIs) associated with 1°C increase in temperature variability. Using the relative risk (RR) of hospitalisation associated with 1°C increase in temperature variability, this indicator can be calculated as $100 \times (RR-1)\%$.[2,10]

At the second stage, we pooled the city-specific estimates for all cities or cities in different socioeconomic groups (Q1–Q4 of each socioeconomic indicator, or classification according to World Bank standard), using a random-effect meta-analysis with maximum likelihood estimation.[23] This gave us the pooled estimation of the association between temperature variability and hospitalisation at the national level and for different socioeconomic strata.

Finally, we used meta-regression to quantify the relationship between city-specific effect estimates and the four socioeconomic indicators. Since the four socioeconomic indicators showed moderate to strong correlations with each other (Pearson correlation coefficients 0·40–0·84; all p values<0·001; appendix 2 p 5), we evaluated their modification effects separately to

	Number of cities	Number of cases	Increased hospitalisation risk, % (95% CI)	p values for difference*
Literacy rate quartiles				
Q1 (lowest)	454	15344354	0·80 (0·70–0·89)	Ref
Q2	453	23313694	0·61 (0·55–0·67)	0·0018
Q3	453	29918657	0·57 (0·53–0·62)	<0·0001
Q4 (highest)	454	79382538	0·43 (0·40–0·46)	<0·0001
Urbanisation rate quartiles				
Q1 (lowest)	454	14195131	0·63 (0·55–0·71)	Ref
Q2	453	16761150	0·56 (0·50–0·63)	0·21
Q3	453	24471426	0·53 (0·48–0·58)	0·030
Q4 (highest)	454	92531536	0·49 (0·45–0·52)	0·0010
Average household income quartiles				
Q1 (lowest)	458	15021111	0·77 (0·67–0·86)	Ref
Q2	449	25296158	0·59 (0·53–0·65)	0·0019
Q3	456	30011571	0·52 (0·48–0·57)	<0·0001
Q4 (highest)	451	77630403	0·46 (0·43–0·49)	<0·0001
GDP per-capita quartiles				
Q1 (lowest)	454	15983538	0·69 (0·60–0·79)	Ref
Q2	453	27860410	0·59 (0·54–0·64)	0·060
Q3	453	37544498	0·53 (0·49–0·58)	0·0026
Q4 (highest)	454	66570797	0·45 (0·42–0·48)	<0·0001
GDP per-capita classifications				
Lower-middle income	832	38223147	0·63 (0·58–0·69)	Ref
Upper-middle income	892	89366536	0·50 (0·47–0·53)	<0·0001
High income	90	20369560	0·39 (0·33–0·46)	<0·0001
Overall	**1814**	**147959243**	**0·52 (0·50–0·55)**	

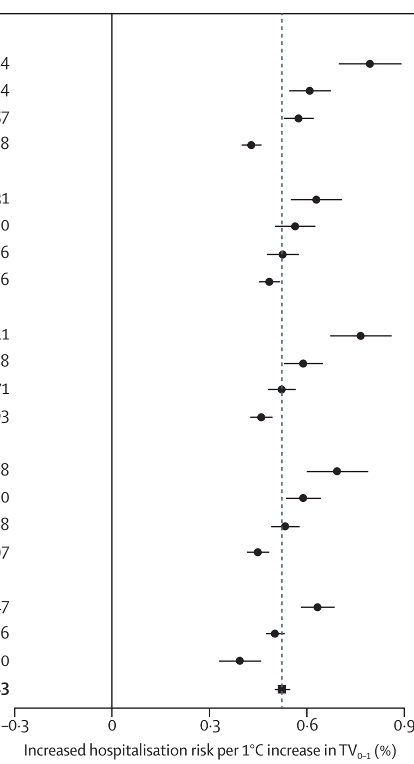

Figure 2: **Association between every 1°C increase in TV_{0-1} and risk of all-cause hospitalisation, stratified by socioeconomic level**
GDP per-capita classifications were based on the World Bank standard in 2015. TV_{0-1}=temperature variability exposure for the current and previous day. Q1–Q4=lowest to highest quartiles of each city-level indicator. Ref=reference. GDP=gross domestic product. *p values for difference tested the difference in relative risks between subgroups, estimated by meta-regression.

avoid co-linearity; specifically, literacy rate, urbanisation rate, household income, and log(GDP per capita) were added to the meta-regression model separately. In the meta-regression models, we controlled for the city-specific characteristics that could affect residents' vulnerability to temperature variability. These characteristics included mean temperature, mean $TV_{0–1}$, and the ratio of young population (aged 0–19 years) and older population (aged ≥60 years). The modification effects of local socioeconomic indicators on the association between temperature variability and association were quantified as the change in log (RR) and its 95% CI when each socioeconomic indicator increased from the 25th percentile to the 75th percentile. Finally, we stratified all these analyses by sex and four age groups (0–19 years; 20–39 years; 40–59 years; and ≥60 years).

To make our results easy to follow, the main results focus only on $TV_{0–1}$, which shows the strongest association with hospitalisation among $TV_{0–1}$ to $TV_{0–7}$ in all five Brazilian regions, as reported by our previous study.[10] In sensitivity analyses, we repeated our main results using $TV_{0–2}$ to $TV_{0–7}$.

We did all data analyses with R software (version 3.5.1). The dlnm package was used for the first-stage analysis and the mvmeta package for the second-stage analysis.[23,24] The Cochran Q test and the I^2 statistic were used to quantify the residual heterogeneity in the meta-regression. A two-side p value of less than 0·05 was considered statistically significant.

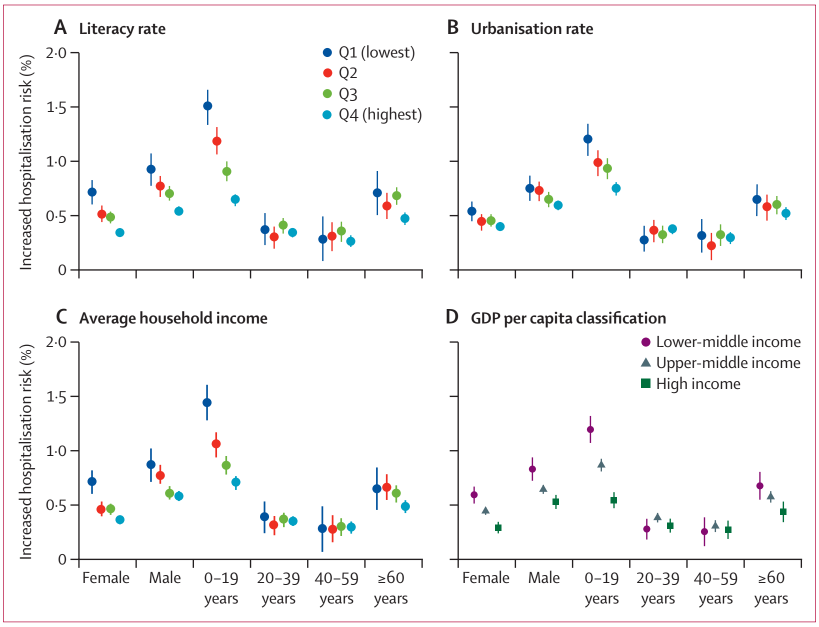

Figure 3: **Association between every 1°C increase in $TV_{0–1}$ and risk of all-cause hospitalisation, stratified by socioeconomic level, sex, and age group**
Graphs show point estimates with error bars for 95% CIs. GDP per-capita classifications were based on the World Bank standard in 2015. $TV_{0–1}$=temperature variability exposure for the current and previous day. Q1–Q4=lowest to highest quartiles of each city-level indicator. GDP=gross domestic product.

Role of the funding source

There was no funding for this study. YG and SL had full access to all the data and were responsible for the decision to submit for publication.

Results

We included a total of 147 959 243 hospitalisations (59·0% female) from 1814 Brazilian cities between Jan 1, 2000, and Dec 31, 2015 (table). The median $TV_{0–1}$ of the 1814 cities was 6·1°C (IQR 5·0–7·3°C) during 2000–15, which ranged from 5·6°C (IQR 4·8–6·7°C) in the north to 6·9°C (IQR 5·8–8·2°C) in the central west (table). A large socioeconomic disparity among the 1814 cities was observed. At the city level, the 16-year average urbanisation rate varied from 8·4% to 100·0%; the average monthly household income per capita in 2010 varied from \$67 to \$729 (in 2015 prices); and the 16-year average GDP per capita varied from \$978 to \$83 307 (in 2015 prices; appendix 2 pp 13–89). In general, compared with northern cities, southern cities were wealthier (higher household income and GDP per capita), more urbanised, and had more educated residents (ie, a higher literacy rate). Southern cities also had an older population structure, with a higher proportion of older people (aged ≥60 years) and a lower proportion of younger people (0–19 years; table; figure 1; appendix 2 pp 13–89).

At the national level, we estimated that every 1°C increase in $TV_{0–1}$ was associated with a 0·52% (95% CI 0·50–0·55; RR 1·0052 [1·0050–1·0055]) increase in risk of hospitalisation (figure 2). The association between temperature variability and hospitalisation was stronger in cities with lower literacy rates, urbanisation rates, household incomes, and GDP per capita than in cities with higher levels of those socioeconomic indicators (figure 2). With largely overlapping 95% CIs of the effect estimates for the quartiles, the modification effect of urbanisation rate was weaker than that of the other socioeconomic indicators (figure 2). The increased hospitalisation risk associated with every 1°C increase in $TV_{0–1}$ was 0·63% (0·58–0·69) for cities of lower-middle income, 0·50% (0·47–0·53) for cities of upper-middle income, and 0·39% (0·33–0·46) for high-income cities (figure 2).

The socioeconomic disparities in the association between temperature variability and hospitalisation were generally similar between women and men. However, when stratified by age groups, the socioeconomic disparities were particularly significant in young people (ie, aged 0–19 years; increased hospitalisation risk 1·21% [95% CI 1·11–1·31] for lower-middle income *vs* 0·52% [0·41–0·63] for high income) and in older people (ie, aged ≥60 years; increased hospitalisation risk 0·60% [0·50–0·70] *vs* 0·43% [0·31–0·56]; figure 3D). No clear socioeconomic disparity was found in the age groups covering 20–59 years (figure 3). The socioeconomic disparities in the vulnerability to temperature variability were mainly evident for infectious diseases (increased hospitalisation risk 1·62% [1·46–1·78] in lower-middle income *vs* 0·56% [0·30–0·82] for high income), respiratory diseases (increased hospitalisation risk 1·32% [1·20–1·44] *vs* 0·55% [0·37–0·74]), and endocrine diseases (increased hospitalisation risk 1·21% [0·99–1·43] *vs* 0·32% [0·02–0·62]; figure 4; appendix 2 pp 6–8).

After adjusting for city-level mean temperature, mean TV_{0-1}, and population structure by meta-regression, the city-specific RRs still showed significant negative

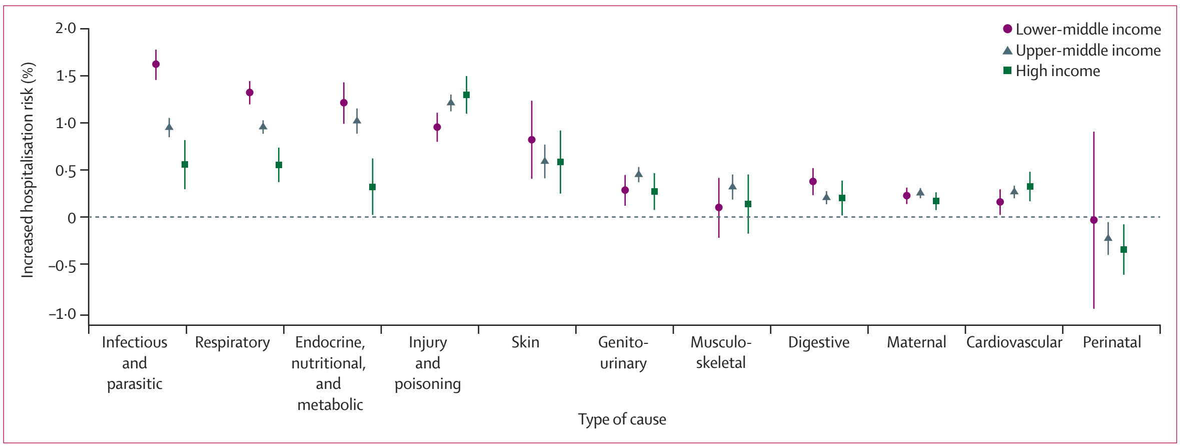

***Figure 4:* Association between every 1°C increase in TV_{0-1} and risk of cause-specific hospitalisation, stratified by GDP per-capita level**
Point estimates shown with error bars for 95% CIs. GDP per-capita classifications were based on the World Bank standard in 2015. TV_{0-1}=temperature variability exposure for the current and previous day. GDP=gross domestic product.

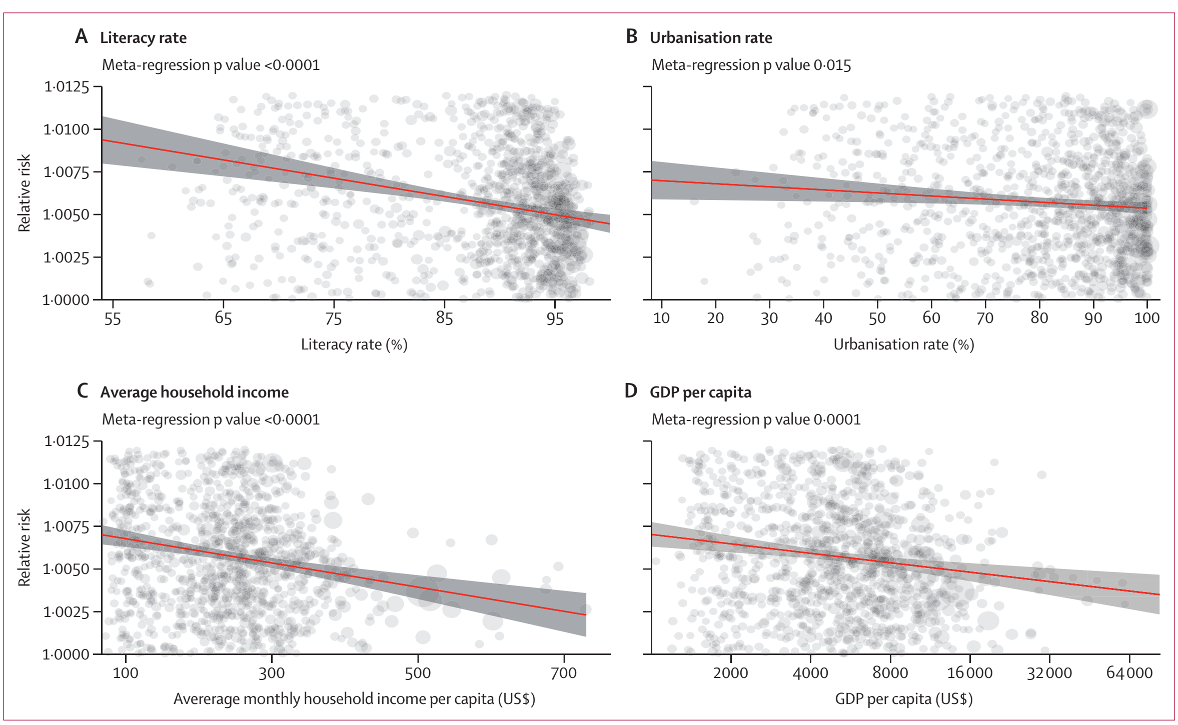

***Figure 5:* Relationship between city-level socioeconomic indicators and effect estimates of the association between temperature variability and hospitalisation**
RR represents the association between every 1°C increase in TV_{0-1} and all-cause hospitalisation. We fitted the relationship between city-specific log(RR) and four socioeconomic indicators separately by meta-regression, adjusting for city-specific mean temperature, mean TV_{0-1}, and the ratio of older population (aged ≥60 years) to young population (aged 0–19 years). The RRs in the figures were predicted as the values when city-specific mean temperature, mean TV_{0-1}, and the ratio of older to young population were at the average level of 1814 cities. The x-axis of figure 5D is on a log scale, because we added log(GDP per capita) rather than GDP per capita to the meta-regression model. The grey dots represent city-specific RRs, with the size of dots being proportional to the city-specific number of hospitalisations (range 12 674–8 693 132; median 33 474 [IQR 23 162–62 207]) included for analyses. RR=relative risk. TV_{0-1}=temperature variability exposure for the current and previous day. GDP=gross domestic product.

associations with the literacy rate (p<0·0001), urbanisation rate (p=0·015), average family income (p<0·0001), and log(GDP per capita) (p=0·0001; figure 5). Similar to figure 2, the modification effect of urbanisation rates in figure 5 seems to be weaker than for the other three socioeconomic indicators. Further meta-regression stratified by sex, age, and diseases supported the finding that socioeconomic inequality was significant mainly for young and older people (appendix 2 p 9), and for infectious, respiratory, and endocrine diseases (appendix 2 p 10).

We repeated our main results using TV_{0-2} to TV_{0-7} as sensitivity analyses, which gave similar results to TV_{0-1} (appendix 2 pp 11–12).

Discussion

To our knowledge, this study is by far the largest and most comprehensive study to evaluate socioeconomic inequality in the association between temperature variability and hospitalisation. We found that people living in cities with lower literacy rates, urbanisation rates, average household income, and GDP per capita were more vulnerable to hospitalisation related to short-term temperature variability. This inequality in vulnerability was particularly significant in young and older people, and for hospitalisation due to infectious, respiratory, and endocrine disease.

There are several potential explanations for the observed socioeconomic inequality in vulnerability, which are mainly related to actual exposure level, sensitivity to temperature variability, and adaptation capacity. First, people in rural or undeveloped areas are likely to do outdoor work (eg, farming or construction).[25–27] This work might mean they are exposed to higher actual temperature variability than those working in climate-controlled settings with air-conditioners. Second, national surveys in Brazil have found that less educated people were more affected by chronic conditions such as diabetes and asthma.[28,29] These chronic conditions could impair people's physiological thermoregulatory functioning[30] and consequently increase their sensitivity to morbidity related to temperature variability. The poor living and sanitation conditions of disadvantaged people might also increase their sensitivity to infectious diseases related to temperature changes (eg, influenza[31]). Third, people living in disadvantaged areas might also have a lower capacity to adapt to temperature variability. For example, they might not have the budget for air-conditioners and heating, or a good house with proper climate regulation. They might also not have sufficient knowledge or health awareness to tackle temperature changes properly.[25] Additionally, disadvantaged areas could have a scarcity of high-quality general health-care services to prevent excess hospitalisation.

Our findings are generally consistent with two studies in China,[7,9] which found that the association between temperature variability and mortality was stronger in rural areas and those with less educated residents. However, Zhang and colleagues[8] found this association to be stronger in urban residents, and provided a plausible explanation for the higher vulnerability in urban areas: the urban heat island (UHI) effect. Briefly, the UHI effect is to raise nocturnal temperatures in urban areas, making the intra-day temperature variability lower than in rural areas.[32] As a result, urban residents who get accustomed to relatively low temperature variability might be more sensitive to changes in temperature variability than rural residents are. This theory was partly supported by a recent study in Japan,[3] which found that the association between temperature variability and mortality increased with population density (a proxy for urbanisation). Although we believe that the UHI effect could have an important role in the vulnerability to temperature variability, other important factors, such as occupation, education, income, living conditions, and health-care services, should not be underestimated. The inconsistency among the current studies,[2,7–9] including ours, might be explained by the different balance between the UHI effect and other important factors in different settings. In Brazil, with the increased urbanisation rate, the potential of an enhanced association between temperature variability and hospitalisation due to the UHI effect was probably offset by other factors, such as increased education, improved income, and better living conditions in those areas. This offsetting might be why an increased urbanisation rate still significantly reduced the association between temperature variability and hospitalisation in our study. It might also explain why the modification effect of urbanisation rate tended to be weaker than the other three socioeconomic indicators. However, more studies with good controls for different socioeconomic factors are needed to test our hypothesis.

Compared with previous studies, we provided more information on the modification effect of local socioeconomic levels on the association between temperature variability and hospitalisation by stratifying the analyses by sex, age, and diseases. In the current study, the modification effect was consistent across different sexes. However, it was only significant in young and older people, but not in people aged 20–59 years. Our previous study[10] suggested that young and older people were the most vulnerable to temperature variability, possibly due to their immature or decreased thermoregulatory functioning. In the current study, we also found that the socioeconomic inequality in the association between temperature variability and hospitalisation was mainly concentrated in infectious, respiratory, and endocrine diseases, but not in other diseases such as cardiovascular diseases. This finding could explain why Tian and colleagues' study[2] (which focused on cardiovascular hospitalisation) did not find a significant modification effect of local GDP per capita on the association between temperature variability and hospitalisation. However, why the socioeconomic inequality pattern varied according to disease remains unknown, and more studies are needed to answer this question. Our results suggest that young and older people in disadvantaged areas should be the target population for additional interventions (eg, health education) or investment to reduce the socioeconomic disparity in temperature variability-related hospitalisations.

The public health implications of the present study are mixed. On the one hand, the inter-city socioeconomic disparities in the vulnerability to short-term temperature variability could exacerbate existing health and economic inequality in Brazil. As we reported previously,[10] 3·5% of hospitalisations could be attributed to temperature variability in Brazil during 2000–15. According to the current study, temperature variability-related hospitalisation burdens in less developed cities tend to be much higher, which could cause considerable excess health-care costs and negatively affect local economic growth. Therefore, more investment should be channelled to undeveloped areas, to improve their ability to adapt to short-term temperature fluctuations. Those actions might include, but are not restricted to, improving living or sanitation conditions, educational level, and health awareness of residents in undeveloped Brazilian cities.

On the other hand, our study suggests potential good news for adaptation to temperature fluctuations, in that the association between temperature variability and hospitalisation might diminish as the economy grows. A long-term decrease in the association between temperature variability and hospitalisation has been reported in Japan[3] during 1972–2015 and in England and Wales[33] during 1993–2006. Unfortunately, this idea must be treated with caution, because we still do not know what factors contributed to the socioeconomic disparities in associations between temperature variability and hospitalisation, due to insufficient relevant data, such as on access to air-conditioners and heating, living and sanitation conditions, access to high-quality health-care services and medications, and knowledge about the health effects of temperature. Another concern is that our study, which is based on city-level socioeconomic indicators, cannot account for intra-city socioeconomic disparities. It is possible that city-wide economic growth only benefits some already high-income residents, rather than the majority of residents within a city. In this scenario, economic growth is not likely to improve most residents' capacity to adapt to temperature variability. Our previous study[10] found that the association between temperature variability and hospitalisation actually increased from 2000 to 2015 in Brazil, although this country had experienced rapid economic growth during the same period (GDP per capita grew from $3147 to $9812[34]). It is possible that the benefits of economic growth were offset by the population ageing,[35] increasing prevalence of non-communicable diseases,[28] and the persistently high levels of income inequality in Brazil.[36]

Our current study has several advantages. First, to our best knowledge, this is by far the largest study to examine the role of socioeconomic inequality in the association between temperature variability and hospitalisation. The large number of locations (1814 cities), 16-year study period, and huge sample size (nearly 150 million hospitalisations) ensured the robustness of our results. Second, the national hospitalisation dataset, which covers nearly 80% of Brazil's population, represents Brazil well. Third, our results might also provide an important reference for other middle-income and high-income countries, given the large diversity in the socioeconomic levels of the cities.

Several limitations should be acknowledged, however. First, the use of gridded city-level temperature data rather than personal measurements might underestimate the association between temperature variability and hospitalisation due to non-differential misclassification. Second, we were unable to adjust for relative humidity and air pollution because of the unavailability of relevant data for most cities. Our previous publication[10] reported that adjustment for relative humidity in a subsample of 265 cities had only a minimal effect on the association between temperature variability and hospitalisation. The adjustment for air pollution is not sufficiently justified; because temperature affects air pollution rather than the reverse, air pollution is more likely to be a mediator rather than a confounder in the association between temperature variability and hospitalisation.[37] Moreover, in a recent study,[2] the association between temperature variability and hospitalisation decreased but remained significant after adjusting for air pollution. Third, due to the unavailability of hourly temperature data, our temperature variability was calculated on the basis of daily maximum and minimum temperatures, rather than using hourly temperatures. However, a recent multicountry study[38] suggested that the associations between temperature variability and mortality based on these two exposure metrics were generally consistent. Our temperature variability definition is also not likely to affect our main findings on the basis of inter-city comparisons, because all cities used the same definition. Fourth, the four socioeconomic indicators in our study were correlated with each other, making it difficult to distinguish and compare the independent modification effect of each indicator. Fortunately, the results from different socioeconomic indicators were largely similar. Finally, this study used city-level socioeconomic data, which cannot evaluate intra-city or individual-level socioeconomic inequality. Further studies with more micro socioeconomic data are needed to fill the knowledge gap on this topic.

In conclusion, people living in less developed cities in Brazil were more vulnerable to temperature variability-related hospitalisation. This effect might exacerbate existing health and socioeconomic inequalities in Brazil. Thus, more efforts should be invested in less developed cities in Brazil to prevent hospitalisations associated with short-term temperature fluctuations.

Contributors

RX, SL, and YG conceived the study and its design. RX, MSZSC, PHNS, SL, and YG contributed to data collection, and QZ contributed to data cleaning. RX did the literature search, data analysis, and drafted the initial manuscript. QZ, SL, and YG refined the data analysis plans and interpretation of the findings. QZ, PHNS, MJA, SL, MSZSC, and YG revised the manuscript. SL and YG have full access to all aspects of the research and writing process and take primary responsibility for the final content.

Declaration of interests

MJA reports speaker's fees from GlaxoSmithKline, consultancy for and conference assistance from Sanofi, and investigator-initiated grants from Pfizer and Boehringer-Ingelheim, all outside the submitted work. All other authors declare no competing interests.

Data sharing

Researchers who are interested in using the data should contact Prof Yuming Guo (yuming.guo@monash.edu) with their study protocol and statistical analysis plan. There will be an assessment for the data request by a committee including stakeholders from the Brazilian Ministry of Health. If approved by the committee, the researcher can gain access to the data, and an agreement on the use of the data may also be needed.

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References

1 Song X, Wang S, Hu Y, et al. Impact of ambient temperature on morbidity and mortality: An overview of reviews. *Sci Total Environ* 2017; **586:** 241–54.
2 Tian Y, Liu H, Si Y, et al. Association between temperature variability and daily hospital admissions for cause-specific cardiovascular disease in urban China: a national time-series study. *PLoS Med* 2019; **16:** e1002738.
3 Ma C, Yang J, Nakayama SF, Honda Y. The association between temperature variability and cause-specific mortality: evidence from 47 Japanese prefectures during 1972–2015. *Environ Int* 2019; **127:** 125–33.
4 Guo Y, Gasparrini A, Armstrong BG, et al. Temperature variability and mortality: a multi-country study. *Environ Health Perspect* 2016; **124:** 1554–49.
5 Watts N, Amann M, Ayeb-Karlsson S, et al. The *Lancet* Countdown on health and climate change: from 25 years of inaction to a global transformation for public health. *Lancet* 2018; **391:** 581–630.
6 Benmarhnia T, Deguen S, Kaufman JS, Smargiassi A. Vulnerability to heat-related mortality: a systematic review, meta-analysis, and meta-regression analysis. *Epidemiology* 2015; **26:** 781–93.
7 Hu K, Guo Y, Yang X, et al. Temperature variability and mortality in rural and urban areas in Zhejiang province, China: an application of a spatiotemporal index. *Sci Total Environ* 2019; **647:** 1044–51.
8 Zhang Y, Yu C, Bao J, Li X. Impact of temperature variation on mortality: an observational study from 12 counties across Hubei Province in China. *Sci Total Environ* 2017; **587:** 196–203.
9 Yang J, Zhou M, Li M, et al. Vulnerability to the impact of temperature variability on mortality in 31 major Chinese cities. *Environ Pollut* 2018; **239:** 631–37.
10 Zhao Q, Coelho MSZS, Li SS, et al. Spatiotemporal and demographic variation in the association between temperature variability and hospitalizations in Brazil during 2000–2015: a nationwide time-series study. *Environ Int* 2018; **120:** 345–53.
11 Zhao Q, Coelho MSZS, Li S, et al. Temperature variability and hospitalisation for cardiac arrhythmia in Brazil: a nationwide case-crossover study during 2000–2015. *Environ Pollut* 2019; **246:** 552–58.
12 Zhao Q, Li S, Coelho MSZS, et al. Temperature variability and hospitalization for ischaemic heart disease in Brazil: a nationwide case-crossover study during 2000–2015. *Sci Total Environ* 2019; **664:** 707–12.
13 Zhao Q, Coelho MSZS, Li S, et al. Trends in hospital admission rates and associated direct healthcare costs in Brazil: a nationwide retrospective study between 2000 and 2015. *Innovation* 2020; **1:** 100013.
14 Global Burden of Disease Collaborators. Burden of disease in Brazil, 1990–2016: a systematic subnational analysis for the Global Burden of Disease Study 2016. *Lancet* 2018; **392:** 760–75.
15 Xu R, Zhao Q, Coelho M, et al. Association between heat exposure and hospitalization for diabetes in Brazil during 2000–2015: a nationwide case-crossover study. *Environ Health Perspect* 2019; **127:** 117005.
16 Zhao Q, Li S, Coelho M, et al. Geographic, demographic, and temporal variations in the association between heat exposure and hospitalization in Brazil: a nationwide study between 2000 and 2015. *Environ Health Perspect* 2019; **127:** 17001.
17 Xu R, Zhao Q, Coelho M, et al. The association between heat exposure and hospitalization for undernutrition in Brazil during 2000–2015: a nationwide case-crossover study. *PLoS Med* 2019; **16:** e1002950.
18 Nakamura-Pereira M, Mendes-Silva W, Dias MAB, Reichenheim ME, Lobato G. Hospital Information System of the Unified Health System (SIH–SUS): an evaluation of its performance for the identification of maternal near miss. *Cad Saude Publica* 2013; **29:** 1333–45.
19 Machado JP, Martins M, Leite IdC. Quality of hospital databases in Brazil: some elements. *Rev Bras Epidemiol* 2016; **19:** 567–81.
20 Xavier AC, King CW, Scanlon BR. Daily gridded meteorological variables in Brazil (1980–2013). *Int J Climatol* 2016; **36:** 2644–59.
21 Brazilian Institute of Geography and Statistics. 2010 Population Censuses. 2019. https://www.ibge.gov.br/en/statistics/social/income-expenditure-and-consumption/18391-2010-population-census.html?edicao=21738&t=resultados (accessed May 12, 2019).
22 World Bank. World Bank country and lending groups, 2019. 2019. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups (accessed May 12, 2019).
23 Gasparrini A, Armstrong B. Reducing and meta-analysing estimates from distributed lag non-linear models. *Bmc Med Res Methodol* 2013; **13:** 1.
24 Gasparrini A. Distributed lag linear and non-linear models in R: the package dlnm. *J Stat Softw* 2011; **43:** 1–20.
25 Gronlund CJ. Racial and socioeconomic disparities in heat-related health effects and their mechanisms: a review. *Curr Epidemiol Rep* 2014; **1:** 165–73.
26 Kovach MM, Konrad II CE, Fuhrmann CM. Area-level risk factors for heat-related illness in rural and urban locations across North Carolina, USA. *Appl Geogr* 2015; **60:** 175–83.
27 Hu K, Guo Y, Hochrainer-Stigler S, et al. Evidence for urban–rural disparity in temperature–mortality relationships in Zhejiang Province, China. *Environ Health Perspect* 2019; **127:** 037001.
28 Beltran-Sanchez H, Andrade FC. Time trends in adult chronic disease inequalities by education in Brazil: 1998–2013. *Int J Equity Health* 2016; **15:** 139.
29 Malta DC, Bernal RT, de Souza MF, Szwarcwald CL, Lima MG, Barros MB. Social inequalities in the prevalence of self-reported chronic non-communicable diseases in Brazil: national health survey 2013. *Int J Equity Health* 2016; **15:** 153.
30 Hajat S, Haines A, Sarran C, Sharma A, Bates C, Fleming LE. The effect of ambient temperature on type-2-diabetes: case-crossover analysis of 4+ million GP consultations across England. *Environ Health* 2017; **16:** 73.
31 Lowen AC, Mubareka S, Steel J, Palese P. Influenza virus transmission is dependent on relative humidity and temperature. *PLoS Pathog* 2007; **3:** 1470–76.

32 Heaviside C, Macintyre H, Vardoulakis S. The urban heat island: implications for health in a changing environment. *Curr Environ Health Rep* 2017; **4:** 296–305.

33 Zhang Y, Yu Y, Peng M, Meng R, Hu K, Yu C. Temporal and seasonal variations of mortality burden associated with hourly temperature variability: a nationwide investigation in England and Wales. *Environ Int* 2018; **115:** 325–33.

34 World Bank. GDP per capita, 2019. 2019. https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=BR (accessed May 12, 2019).

35 Cuevas MA, Karpowicz MI, Mulas-Granados MC, Soto M. Fiscal challenges of population aging in Brazil. Washington, DC: International Monetary Fund, 2017.

36 Signor D, Kim J, Tebaldi E. Persistence and determinants of income inequality: the Brazilian case. *Rev Dev Econ* 2019; **23:** 1748–67.

37 Buckley JP, Samet JM, Richardson DB. Does air pollution confound studies of temperature? *Epidemiology* 2014; **25:** 242–45.

38 Zhang Y, Xiang Q, Yu C, et al. Mortality risk and burden associated with temperature variability in China, United Kingdom and United States: comparative analysis of daily and hourly exposure metrics. *Environ Res* 2019; **179:** 108771.