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Mortality due to heatstroke and exposure to cold: Evidence from India

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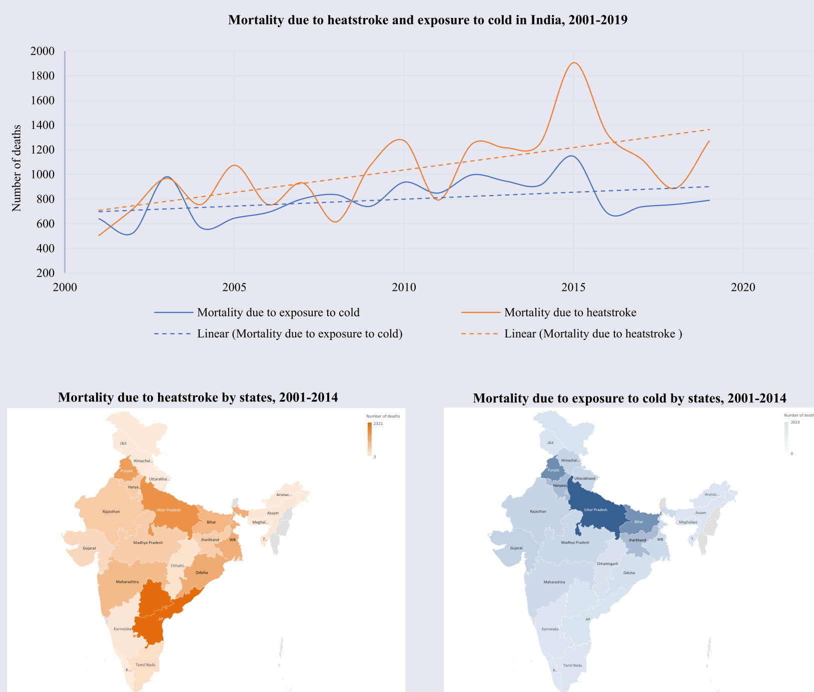
ABSTRACT

The effects of exposure to extreme heat and cold temperatures on human health have mostly been studied in high-income countries. We examined this association by exploring the effect of extreme temperatures on mortality due to heatstroke and exposure to cold in India and by states. We used temperature data from the Indian Meteorological Department (IMD) and mortality data from the National Crime Records Bureau (NCRB) to examine trends in overall, gender, and age-specific mortality. We used structural breaks analysis to observe changes in India's mortality trends during 2001–2019. We examined the time trends in the relationship between extreme temperature and mortality for 24 Indian states from 2001 to 2014. We used panel regression and spline regression models. Between 2001 and 2019, India reported 19,693 and 15,197 deaths due to heatstroke and cold exposure, respectively. Top three states with the greatest number of deaths due to heatstroke were Andhra Pradesh, Uttar Pradesh, and Punjab; for cold exposure it was Uttar Pradesh, Punjab, and Bihar. Working-age men were significantly more susceptible to heatstroke. Spline regression results indicated that mortality varied across different temperature bins for both extreme summer and winter temperatures. Our findings demonstrate an urgent need to strengthen welfare and social support systems and invest in built environment and livelihood interventions to counter the avoidable mortality from extreme temperature events.



Notes: Heat maps created using Microsoft Excel. Telangana is combined with Andhra Pradesh (AP), Ladakh is combined with Jammu & Kashmir (J&K)

Source: Authors' computation based on NCRB data.

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Introduction

The global rise in extreme weather events, especially heat and cold waves, has been linked to health, livelihoods, and wellbeing of populations [1–3]. There is a growing recognition that exposure to extreme heat and cold temperatures can lead to physiological effects on human health, especially cardiovascular health and respiratory health, that may lead to premature mortality [4–7]. Research has documented these associations of heat and cold wave mortality across developed nations such as the USA [4,8], Russia [9], Sweden [10] and other European countries [11]. While most of these studies have focused on one-off or episodic occurrences of extreme temperature through an annual heatwave or cold wave episode [11,12], few studies have covered a wider timeframe [13–16]. In particular, the impacts of these extreme temperatures have been noted on mortality among the elderly and vulnerable social groups [17,18].

However, increasingly, these extreme weather events linked to global climate change are being noted as recurring annual or seasonal phenomena and not a one-off seasonal anomaly [19]. These recurring extreme temperatures are being noted to be growing in both frequency and intensity, and there is a need to study their effects over time on human health. In particular, the effects of these extreme temperatures on health and mortality remain understudied in low- and middle-income countries (LMICs) like India, where welfare support measures to counter their effects may be lagging.

A major concern in these contexts has been the silo-ed nature of climate change mitigation efforts, including knowledge generation on the pathways to health, and in identifying joint areas for action. Hence, as a response, the World Health Organization (WHO), in a 2023 report, emphasized the inclusion of health within national climate change priorities and programs [20]. This framework necessitates an urgent need for evidence and action to understand the relationships between climate change and health adaptation and resilience [20]. Further, it has laid the groundwork for identifying key action areas that can shape national and sub-national/local action plans [21,22]. Other than direct effects on population wellbeing, these extreme weather events can affect livelihoods, agriculture, and other large-scale population patterns including migration [23,24]. Further, in addition to their physiological effects, there is also a need to understand their effects on mental health [25,26].

India's size and geographic and topographical variations lend itself to a variety of seasons and climates, making it prone to extreme heat and cold temperatures. Given India's geolocation and climate, there has been wide recognition of the risks of heat-related events rather than cold-related; however, parts of the country also experience extreme cold temperatures. Several states and India's national meteorological department have initiated seasonal advisories to forewarn populations on upcoming heat and cold waves along with drafting recommended action plans for adaptation [27,28]. Local initiatives such as the Ahmedabad Heat Action Plan (HAP) have offered useful municipal-level solutions to alleviate the distress caused by extreme weather events [21]. However, to draft a comprehensive response plan and to understand specific needs related to adaptation and resilience, there is a need to understand population-level effects of extreme temperature both nationally and across states, as well as over time.

Three major gaps can be noted in our understanding of the relationship between extreme temperatures and health, specifically mortality. *First*, we need to systematically examine the vulnerability to heat and cold-associated mortality, including gender- and age-related disparities in risk, and the states and regions that are most affected. *Second*, there is a need to assess the relationship between extreme temperatures and mortality and whether and how it might be changing over time. And *third*, the role of welfare spending and other determinants in influencing the relationship between extreme temperature and mortality remains unexplored, which needs careful examination. This study aimed to examine these questions to understand the distribution of heat- and cold-related mortality in India, and its variation by gender and age. It examined time trends in the relationship between extreme summer and winter temperature and mortality, to understand shifts in mortality over time. In doing so, we also investigated the role of welfare spending and social-sector utilization as markers of state capacity in influencing the relationship. To the best of our knowledge, this is a first-of-its-kind study that attempts to understand the impact of exposure to extreme heat and cold temperatures on mortality from a pan-India perspective. This evidence can aid national and state climate action programs to identify points of vulnerabilities within their regions and populations, and to invest in strategies to alleviate the stress and hazards related to extreme temperature.

Materials and methods

Data

We created the analytical dataset by compiling data from multiple publicly available secondary data sources. We used this dataset to conduct a national-level analysis with 19 y (2001–2019) and state-level analysis with 14 y (2001–2014) of data. The separate period of analysis for country- and state-level was due to variability in the availability of data. While detailed mortality data, by age and gender, were publicly available at the national-level for the 19-y period (2001–2019), such granular data at the state-level were only available for the 14-y period (2001–2014).

We used temperature data from the India Meteorological Department (IMD), under the Ministry of Earth Sciences, Government of India, and data on mortality due to heatstroke and exposure to cold from the National Crime Records Bureau (NCRB), under the Ministry of Home Affairs, Government of India. Both agencies are nodal agencies in the respective field and lead data collection and analysis for temperature and mortality, respectively. We also collected temperature data for a few years for Delhi from an online portal www.weatheronline.in, as it was not readily available from IMD. There was no significant variation in temperature data from both the sources. Additionally, we used data on health expenditure and social-sector expenditure from the Reserve Bank of India (RBI), a central bank responsible for monetary policy, and urban population statistics from the Office of the Registrar General and Census Commissioner, under the Ministry of Home Affairs, Government of India.

Dependent variables data

Our dependent variables are extreme temperature-related mortality, classified as deaths due to exposure to cold and heatstroke, by gender and age-group. Exposure to cold is self-explanatory. Heatstroke, which is common during summer months, is a condition due to body overheating when we are exposed to high temperatures or perform physical activity in high temperatures for a long period. We obtained mortality data related to exposure to cold and heatstroke from NCRB, which produces this information through their publicly available annual publication titled the Accidental Deaths and Suicides in India (ADSI) [29]. NCRB is the nodal agency offering a comprehensive state-level collation of mortality data from exposure to natural causes, including those related to exposure to cold and heatstroke. These data are aggregated using a standard proforma that collate medically verified data through city- and district-level police records. The head of administration of each district, called the District Collector or District Magistrate, then shares these mortality data with the State Crime Records Bureau (SCRB), where it is aggregated at the state-level. Proforma can aggregate information by gender and age-group. Although NCRB also provided mortality data at the city-level, due to the non-availability of city-level data for most of the independent variables (discussed later), we focused our analysis only at the national- and state-levels. For state-level analysis, we focused only on those states where the cumulative mortality rate in every state over the 14-y period was more than nine deaths each, either due to exposure to cold or heatstroke. This left us with testing the hypotheses at the state-level for 24 states in India,[1] including Delhi. These states represent approximately 98% of the Indian geographical landmass and 99% of its population.

In the absence of year-wise, state-level, publicly available data on either cause-specific or all-cause mortality, we believe that mortality estimates provided by NCRB could help us explore the association between exposure to extreme temperature and mortality. As NCRB data are sourced from police records, we believe that these estimates may not cover the complete spectrum on mortality due to exposure to extreme temperatures, as captured by deaths due to heatstroke and exposure to cold [30,31]. As such, these estimates, and our results on association, should be considered as conservative in nature, typically on the lower side.

Independent variables of interest data

We obtained monthly state-level maximum and minimum temperature data for all states for the period 2001–2019, except Delhi, from IMD. For Delhi, for a few years, we obtained this data from an online portal www.weatheronline.in. We computed extreme temperature as the average summer maximum temperature (*asmt*) and the average winter minimum temperature (*awmt*). We computed a simple average of three-monthly maximum and minimum temperatures for the three summer months (April, May, and June) and winter months (January, February, and December) in a calendar year, respectively. These average temperatures, in degree Celsius (°*C*), comprised our primary variables of interest.

Other independent variables data

We obtained health expenditure data (*exp_health*), defined as expenditure on medical and public health and family welfare as a ratio of aggregate expenditure (in percent), from the Reserve Bank of India's (RBIs) annual publication titled *State Finances: A Study of Budget* [32]. We used the same source to obtain estimates related to budget allocation and actual expenditure made under social sector, which includes medical and public health. We used these estimates to compute the utilization rate of social-sector expenditure as a ratio of actual expenditure to budget allocation (*util_rate_sse*).

We collected data on the percent urban population (*pct_urban*) from the Office of the Registrar General & Census Commissioner, Government of India. Based on our assumption that the reporting on mortality due to extreme temperatures across Indian states would predominantly be from urban areas; hence, we included the percentage of urban population as an explanatory variable. In addition, we included health expenditure [33,34] and utilization rate [35] variables due to their associations with mortality.

Statistical analysis

Country-level analysis

For country-level analysis, first, we compared the trends in overall, gender, and age-specific mortality due to exposure to extreme temperatures. Next, we used a modified version of the Bai-Perron (BP) structural breaks technique, as proposed by Kar et al., to observe any change in mortality trends during the 19-y study period [36,37]. Structural breaks (i.e. up-breaks or down-breaks) in large time-series data allowed for capturing sudden and permanent changes outside of the model to explain the relationship between variables in the model [37]. In our case, we used this technique to identify structural breaks in the trajectories of mortality due to heatstroke and cold exposure, separately. The break years helped in identifying any significant change in the growth rate of mortality due to heatstroke and exposure to cold vis-à-vis summer and winter extreme temperatures, respectively. This would provide helpful information for better policymaking.

The technique follows a two-step method. The first step was to identify the maximum number of possible breaks. The test then employed a sequential approach to identify statistically significant break years in the second phase. It assumes that the data series had a single structural break and tested for equality between the regression parameters in the two segments. The sample was split into two sub-samples, and the same process was performed for each sub-sample if the test rejected the null hypothesis of a single break. This sequential approach is repeated until the test rejected the null hypothesis and revealed a structural break. The break years in this technique were determined by finding the dynamic programming algorithm's global minimizer of the residual sum of squares of linear regression. However, this technique may not be able to identify a genuine number of breaks in the shorter samples as compared to the larger samples, especially for data series that are highly volatile [36]. This is known as the "true negative" problem, and it indicates the "low power" of the Bai-Perron (BP) test [37]. To overcome this problem, Kar et al. proposed the "fit and filter" approach which also works as a two-step mechanism [36]. The first step used the BP estimation technique to identify potential breaks. However, the second step uses an economic filter instead of a statistical procedure to confirm the genuine breaks.[2] We used the StrucBreak package of Gretl software, version 0.91 to identify structural breaks [38], by allowing a maximum of two breaks with a gap of minimum 5 y in our study period controlling for heteroskedasticity and autocorrelation variance-covariance estimation [36,39].

State-level analysis

We began our state-level analysis by looking at heat maps that demonstrated mortality by states and years. Further, we applied econometric techniques on panel data with a state-year combination as the unit of analysis, to study the association between extreme temperature and mortality. Separately, for each dependent variable, which comprised a set of nine variables for mortality due to heatstroke and cold exposure, respectively, we estimated the following model:

$$M_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 C_{it} + \alpha_i + \lambda_t + u_{it} \qquad (1)$$

where M_{it} is a vector of outcome variables representing extreme temperature-related death in state i - during year t, i.e. total deaths due to heatstroke (*td_h*); deaths among males due to heatstroke (*md_h*); deaths among females due to heatstroke (*fd_h*); deaths among males, aged less than 30 y, due to heatstroke (*md_lt30_h*); deaths among females, aged less than 30 y, due to heatstroke (*fd_lt30_h*); deaths among males, aged 30–59 y, due to heatstroke (*md_30_59_h*); deaths among females, aged 30–59 y, due to heatstroke (*fd_30_59_h*); deaths among males, aged 60 and above years, due to heatstroke (*md_60_h*); and deaths among females, aged 60 and above years, due to heatstroke (*fd_60_h*). Similarly, there are nine outcome variables that represent mortality due to exposure to cold (in all the above variables, "*_h*" is replaced by "*_c*").

T_{it} is a vector representing primary variables of interest in state i during year t, i.e. average summer maximum temperature (*asmt*) and average winter minimum temperature (*awmt*). C_{it} is a set of other independent variables that we include in the model such as expenditure on health (*exp_health*), percent urban population (*pct_urban*) and utilization rate in social-sector expenditure (*util_rate_sse*). α_i and λ_t are the state and year fixed-effects, respectively, and u_{it} is the error term. We used the longitudinal nature of the data to estimate the regression coefficients using a fixed-effects model. This model is controlled for any unobserved time-invariant factor that may otherwise bias the outcome variables by considering each state as its own control. It used within-state variation to estimate the regression coefficients.

We adopted a stepwise approach to arrive at our full model. We began with an unadjusted model. The estimated coefficients based on the unadjusted model (impact of exposure to extreme temperature on mortality) simply indicate the mean difference in heatstroke and cold exposure mortality between those exposed and unexposed to extreme heat and cold temperatures, respectively. In the second step, we included other observed factors that explain mortality among those exposed to extreme temperature. To control for any omitted variable bias due to unobserved factors that vary across states (e.g. spatial factors that influence adaptability to temperature extremes) but are constant over the study period, we introduced the state fixed-effects in the third step. Finally, we included year fixed-effects in our model to control for any omitted factors that are same across all the states but may have changed over time (e.g. any national-level policy to control mortality due to extreme temperature). To maintain brevity, we present the results based on the final (full) model as described above.

In addition, we examined whether exposure to different levels of hot and cold temperature differentially impacted mortality due to heatstroke and exposure to cold, respectively. This is because every one-degree change in temperature is not likely the same and there may be threshold effects of temperature change on mortality. For example, *ceteris paribus*, a one-degree increase in temperature from 46°C to 47°C may have a greater impact on heatstroke mortality than an increase from 29°C to 30°C.

Similarly, a drop in temperature at lower compared to higher temperature levels will have a greater impact on cold exposure mortality. To explore this, we performed two types of analysis. In our first approach, we plotted the number of deaths due to heatstroke and exposure to cold against mean centered summer maximum and winter minimum temperatures and their square terms, respectively. We then regressed total heatstroke deaths to mean-centered average summer maximum temperature and its square factor, and total cold exposure deaths due to on mean-centered average winter minimum temperature and its square factor, along with other covariates.

In our second approach, we explored further on the impact on mortality due to different temperature levels by conducting piecewise regression using the spline function of extreme temperature. We re-estimated the coefficients in model (1) by using linear splines of temperature variables that allowed us to understand the relationship between mortality and various ranges of temperature as a piecewise linear function. We used Stata's **mkspline** command to distribute the average summer maximum temperature (*asmt*) into three categories (*asmt1*: <33°*C*, *asmt2*: 33–38°*C*, *asmt_top*: ≥38°*C*) and the average winter minimum temperature (*awmt*) into four categories (*awmt1*: <5°*C*, *awmt2*: 5–10°*C*, *awmt3*: 10–15°*C*, *awmt_top*: ≥15°*C*). The stratification of the summer and winter temperatures in the above-mentioned categories was based on observing the pattern of two scatter plots. One scatter plot is between total deaths due to heatstroke (*td_h*) and average summer maximum temperature (*asmt*), and the other is between total deaths due to exposure to cold (*td_c*) and average winter minimum temperature (*awmt*). The scatter plots for each temperature type demonstrated a distinct shift in plot patterns around the above-mentioned temperature points. To account for any serial correlation in the error term, we adjusted the standard errors in all the models by clustering at the state level. We used Stata 14.2 [40] and Microsoft Excel to perform our state-level analysis. We assumed statistical significance for $p < 0.05$. As the Stata 14.2 software also generates two other levels of significance ($p < 0.10$ and $p < 0.01$) by default while producing regression output, we have retained them in our tables and result section.

Results

Country-level analysis results

We present the results of country-level analyses in Figures 1 and 2. Mortality in India, in general, due to heatstroke and exposure to cold has increased during the study period, with most deaths recorded in 2015 (Figure 1, Panel *a*). There were more deaths among males compared to females, four to seven times more due to exposure to cold and three to five times more due to heatstroke (Figure 1, Panels *b* and *c*). People in 45–60 y age group were most susceptible to die due to exposure to extreme temperature, followed by the elderly above 60 y and those between 30–45 y (Figure 1, Panels *d* and *e*).

Figure 2 demonstrates the break years of mortality due to extreme temperature exposure type that we obtain following structural break analysis technique [36]. This allowed us to explore the role of changes in temperature in explaining the growth rate of mortality during our study period. We observed two structural breaks each for heatstroke and exposure to cold. Panel a.1 and a.2 present structural breaks for mortality due to exposure to cold, the first break year was in 2005. After 2005, the average winter minimum temperature started falling till the next break year, 2012. During this period, the growth rate of mortality increased significantly, i.e. we see an up-break indicating an increase in mortality due to cold exposure. After 2012, as the average winter minimum temperature increased, mortality decreased significantly, i.e. we observe a down-break. Similar is the observation for mortality due to heatstroke presented in panel b.1 and b.2. As the average summer maximum temperature started increasing after 2008, there

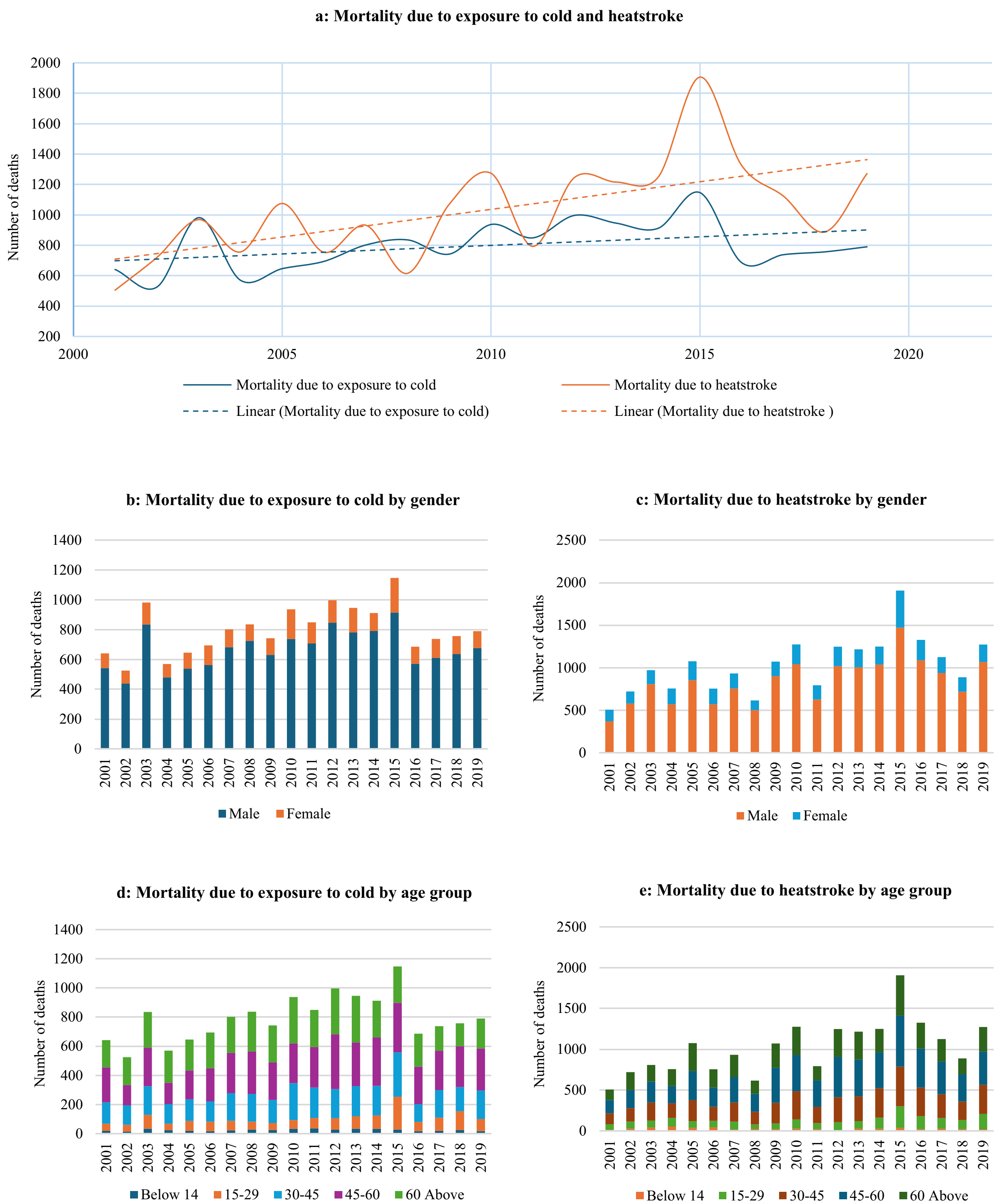
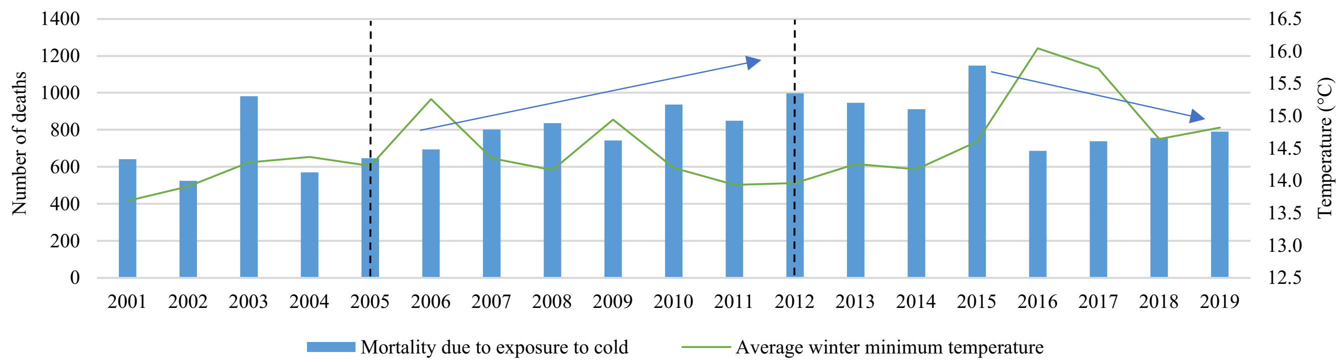


Figure 1. Country-level descriptive analysis, 2001–19.

a.1: Estimation of structural breaks for mortality due to exposure to cold

Year	Average growth rate of mortality due to exposure to cold
2001-2005	1.55%
2006-2012 (up-break)	7.20%
2013-2019 (down-break)	-1.20%

a.2: Mortality due to exposure to cold with break years and temperature



b.1: Estimation of structural breaks for mortality due to heatstroke

Year	Average growth rate of mortality due to heatstroke
2001-2008	5.60%
2009-2013 (up-break)	21.90%
2014-2019 (down-break)	5.30%

b.2: Mortality due to heatstroke with break years and temperature

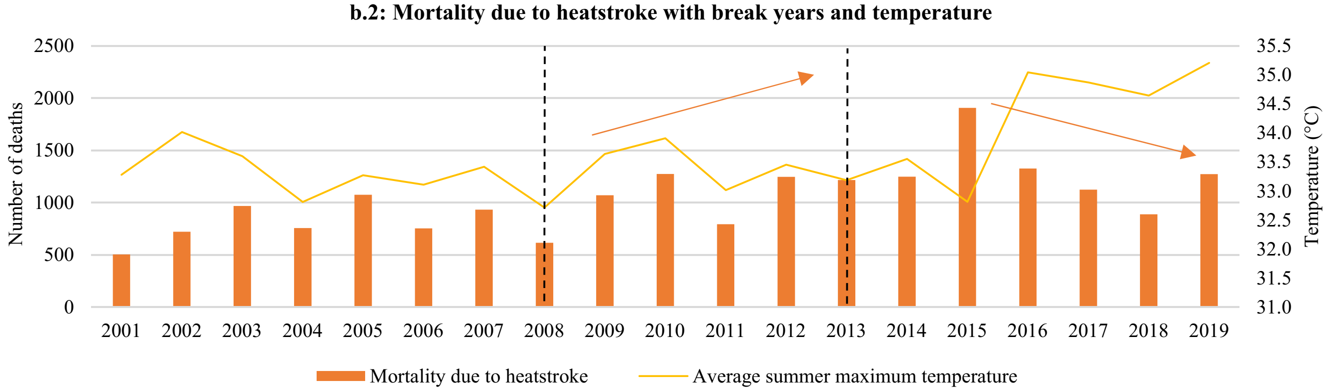


Figure 2. Country-level structural breaks analysis, 2001–19.

Table 1. Descriptive statistics.

Variable	N	Mean	Std. Dev.	Min	Max
Outcome variable:					
Total deaths due to heatstroke (*td_h*)	336	39	53.9	0	418
Male deaths due to heatstroke (*md_h*)	336	31	44.2	0	332
Female deaths due to heatstroke (*fd_h*)	336	8	11.4	0	86
Total deaths due to exposure to cold (*td_c*)	336	33	51.9	0	274
Male deaths due to exposure to cold (*md_c*)	336	27	43.7	0	229
Female deaths due to exposure to cold (*fd_c*)	336	5	10.1	0	62
Deaths due to heatstroke among males below 30 y (*md_lt30_h*)	336	4	5.5	0	44
Deaths due to heatstroke among males between 30 and 59 y (*md_30_59_h*)	336	19	28.5	0	205
Deaths due to heatstroke among males 60 y and above (*md_60_h*)	336	8	12.5	0	97
Deaths due to heatstroke among females below 30 y (*fd_lt30_h*)	336	1	2.0	0	21
Deaths due to heatstroke among females between 30 and 59 y (*fd_30_59_h*)	336	4	6.0	0	45
Deaths due to heatstroke among females 60 y and above (*fd_60_h*)	336	3	4.9	0	34
Deaths due to exposure to cold among males below 30 y (*md_lt30_c*)	336	3	5.6	0	34
Deaths due to exposure to cold among males between 30 and 59 y (*md_30_59_c*)	336	16	26.3	0	145
Deaths due to exposure to cold among males 60 y and above (*md_60_c*)	336	8	14.3	0	88
Deaths due to exposure to cold among females below 30 y (*fd_lt30_c*)	336	1	1.7	0	14
Deaths due to exposure to cold among females between 30 and 59 y (*fd_30_59_c*)	336	2	4.5	0	30
Deaths due to exposure to cold among females 60 y and above (*fd_60_c*)	336	2	5.0	0	34
Independent variable:					
Average summer maximum temperature (*asmt*)	335	34.4	4.6	24.8	41.4
Average winter minimum temperature (*awmt*)	329	11.6	4.4	1.6	20.2
Expenditure on health (*exp_health*)	336	4.4	1.2	2.4	11.7
Percent urban population (*pct_urban*)	336	29.4	16.8	9.8	96
Utilization rate in social sector expenditure (*util_rate_sse*)	336	96.6	16.8	13.1	209.1

All missing observations are from Delhi; one for *asmt* and seven for *awmt*.
Source: Authors' computation using analytical dataset.

was a significant increase in mortality (up-break), following a down break in 2013.

State-level analysis results

The total sample comprised of 336 observations for most variables, except for two extreme temperature-related variables, *asmt* and *awmt* (Table 1). Missing observations were from Delhi, one for *asmt* and seven for *awmt*. During the study period, on an average, more people died due to heatstroke compared to exposure to cold (39 vs. 33). Males were more susceptible to extreme temperature, particularly those in the age group of 30–59 y. Overall, 31 and 27 males died due to heatstroke and exposure to cold, respectively, compared to eight and five deaths among females. Nineteen males compared to four females, in the age group of 30–59 y, died due to heatstroke. The average summer maximum temperature during the study period remained around 34.4°C, ranging between 24.8°C and 41.4°C, while the average winter minimum temperature was recorded around 11.6°C, ranging between 1.6°C and 20.2°C.

Tables 2 and 3 present mortalities by state and year due to heatstroke and exposure to cold, respectively, in the form of heatmaps. The first column in the table containing state names also indicates rank within parentheses; rank 1 indicates state with the highest number of deaths, and so on. The colored cells in the heatmap move from deep red to deep green color, representing the most to least number of deaths. During 2001 and 2014, there were 13,000 deaths due to heatstroke (Table 2) and around 11,000 deaths due to exposure to cold (Table 3). For the study period, Andhra Pradesh, Uttar Pradesh, and Punjab were the top three states with the highest number of

Table 2. Annual number of deaths across states between 2001 and 2014 due to heatstroke.

States (Rank)	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	State-wise total death
Andhra Pradesh (1)	46	80	100	52	105	125	128	124	262	197	91	221	418	372	2321
Arunachal Pradesh (21)	0	0	1	0	0	1	4	5	5	1	0	0	0	0	17
Assam (18)	7	2	4	16	13	7	7	8	0	1	1	1	5	0	72
Bihar (6)	47	22	70	32	68	52	58	28	46	95	86	166	85	131	986
Chhattisgarh (15)	5	20	22	9	14	4	15	7	6	10	3	10	3	4	132
Delhi (13)	28	45	18	20	19	14	26	7	40	41	6	17	2	9	292
Gujarat (12)	24	47	30	12	13	7	16	6	9	58	15	17	26	45	325
Haryana (9)	1	17	2	4	19	13	75	31	34	60	30	95	82	79	542
Himachal Pradesh (20)	2	0	8	0	3	1	0	0	1	0	1	2	0	1	19
Jammu & Kashmir (19)	0	0	3	2	2	2	1	0	0	6	1	0	3	0	20
Jharkhand (11)	2	6	8	19	60	37	38	48	50	49	29	74	42	50	512
Karnataka (16)	2	4	6	7	15	5	1	2	9	15	21	2	6	2	97
Kerala (22)	0	0	4	1	0	0	1	0	1	2	0	0	1	0	10
Madhya Pradesh (10)	8	32	39	158	24	45	41	11	20	46	24	35	12	33	528
Maharashtra (7)	43	50	77	62	69	33	70	30	79	137	41	59	80	58	888
Meghalaya (24)	0	0	0	1	0	0	0	0	0	0	0	0	0	2	3
Odisha (4)	60	77	98	76	94	51	55	69	101	130	51	124	101	78	1165
Punjab (3)	55	39	38	43	87	69	129	64	150	170	176	155	144	123	1442
Rajasthan (8)	19	57	44	37	38	35	56	29	55	54	37	32	40	45	578
Tamil Nadu (14)	27	26	54	14	5	23	14	15	31	18	1	0	0	0	228
Tripura (17)	4	0	2	0	15	5	0	9	10	12	6	0	12	2	77
Uttar Pradesh (2)	52	134	126	95	199	87	108	80	117	118	104	156	108	126	1610
Uttarakhand (23)	0	0	0	0	2	1	2	0	0	0	0	1	0	0	6
West Bengal (5)	66	62	52	96	211	137	86	43	45	54	69	76	45	88	1130
Total death by year	498	720	806	756	1075	754	931	616	1071	1274	793	1243	1215	1248	13000

The colored cells in the heatmap moves from deep red to deep green color, representing most to least number of deaths. Ranks are based on the total number of deaths in a state across the 14-y period.
Source: Authors' computation using NCRB data.

deaths due to heatstroke, while Uttar Pradesh, Punjab, and Bihar were the top three in terms of deaths due to exposure to cold.

Tables 4 through 8 present findings from our regression analyses.

Table 4 demonstrates the association between extreme summer temperature, defined as average summer maximum temperature and mortality due to heatstroke. With a one-degree Celsius increase in the average summer maximum temperature, there were around eight additional deaths, keeping other factors constant ($p < 0.05$). Males were four times more affected compared to females; approximately seven males versus two female deaths ($p < 0.05$). Extreme summer temperature significantly explained heatstroke mortality among males ($p < 0.10$) in the age group of 30–59 y compared to their female counterparts (not significant). Similar findings prevail for extreme summer temperature among the elderly population 60 y and above – for every female death due to heatstroke, there are two more deaths among male ($p < 0.05$).

The negative coefficients of utilization rate of allocated funds under the social sector (*util_rate_sse*) indicated that with increased utilization of social-sector funds, the mortality due to heatstroke decreased. However, only the estimate of female deaths due to heatstroke was statistically significant ($p < 0.10$). Similarly, the negative regression coefficients of percent urban population (*pct_urban*) indicated that as percentage of urban population increased, mortality due to exposure to heatstroke decreased. This coefficient was significant ($p < 0.10$) for deaths among females, including those in the age group of 30–59 y.

Extreme winter temperature, defined as the average winter minimum temperature, has no statistically significant impact on cold exposure mortality, across gender and age-groups, as demonstrated by the regression coefficients of the full model (Table 5). However, the signs of most average winter minimum temperature (*awmt*) coefficients were in the hypothesized direction, i.e. negative, for most unadjusted and adjusted models except those that included year-fixed

Table 3. Annual number of deaths across states between 2001 and 2014 due to exposure to cold.

States (Rank)	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	State-wise total death
Andhra Pradesh (17)	11	0	4	0	5	6	2	2	0	15	7	2	2	0	56
Arunachal Pradesh (18)	1	3	1	2	5	0	4	0	0	1	1	1	2	1	22
Assam (19)	0	0	0	1	0	1	0	0	0	8	0	0	7	0	17
Bihar (3)	27	55	176	72	27	81	97	103	98	156	174	171	180	230	1647
Chhattisgarh (15)	2	1	6	8	4	3	8	7	1	3	7	11	2	7	70
Delhi (6)	143	95	64	38	34	34	68	69	34	39	11	10	9	4	652
Gujarat (7)	31	32	68	38	43	14	25	29	7	20	15	23	31	23	399
Haryana (4)	12	31	31	20	39	29	91	88	60	75	84	98	124	84	866
Himachal Pradesh (8)	13	23	16	19	28	23	20	33	44	13	21	36	37	32	358
Jammu & Kashmir (16)	1	0	3	2	0	11	7	9	5	8	3	4	4	3	60
Jharkhand (5)	9	19	19	33	84	52	74	90	64	70	31	100	89	79	813
Karnataka (21)	1	0	0	0	0	0	0	0	1	0	13	0	0	0	15
Kerala (24)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Madhya Pradesh (11)	20	14	43	13	16	46	5	11	21	14	28	22	17	12	282
Maharashtra (13)	32	19	23	26	22	13	16	17	16	9	8	13	9	4	227
Meghalaya (22)	1	0	0	3	4	0	0	0	0	1	0	0	3	0	12
Odisha (14)	6	3	5	2	7	2	5	2	17	54	2	3	1	4	113
Punjab (2)	79	42	80	80	86	90	145	162	130	190	189	154	195	146	1768
Rajasthan (9)	35	26	28	24	21	22	16	28	26	20	15	28	31	32	352
Tamil Nadu (20)	3	7	0	1	0	3	2	0	0	0	0	0	0	0	16
Tripura (23)	0	0	0	0	0	0	0	0	0	1	1	0	0	0	2
Uttar Pradesh (1)	149	133	231	163	194	176	183	164	173	201	193	274	163	226	2623
Uttarakhand (10)	54	9	22	10	13	22	28	14	39	32	20	25	23	7	318
West Bengal (12)	10	9	15	13	14	66	5	8	5	7	23	22	17	19	233
Total death by year	640	521	835	568	646	694	801	836	741	937	846	997	946	913	10921

The colored cells in the heatmap moves from deep red to deep green color, representing most to least number of deaths. Ranks are based on the total number of deaths in a state across the 14-y period.
Source: Authors' computation using NCRB data.

Table 4. Regression result: association between average summer maximum temperature and mortality due to heatstroke.

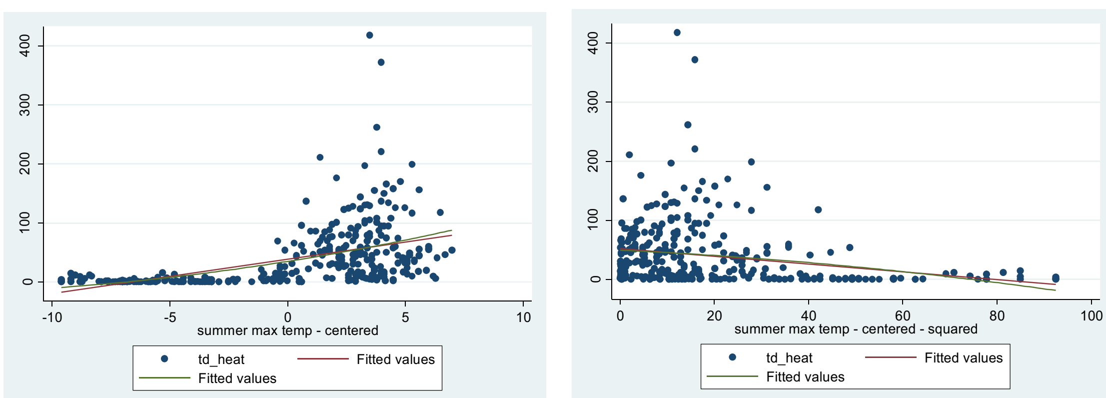
	Dependent variable								
Independent variable	*td_h*	*md_h*	*fd_h*	*md_lt30_h*	*fd_lt30_h*	*md_30_59_h*	*fd_30_59_h*	*md_60_h*	*fd_60_h*
asmt	**8.028****	**6.466****	**1.562****	**0.705***	**0.307****	**3.713***	0.432	**2.047****	**0.824****
	(3.332)	(2.816)	(0.636)	(0.345)	(0.137)	(1.926)	(0.312)	(0.739)	(0.336)
exp_health	−3.108	−2.277	−0.831	−0.501	−0.138	−0.704	−0.299	−1.072	−0.394
	(2.743)	(2.115)	(0.773)	(0.408)	(0.143)	(1.321)	(0.391)	(0.637)	(0.433)
pct_urban	−3.121	−2.030	**−1.091***	−0.030	−0.147	−1.348	**−0.577***	−0.652	−0.368
	(3.205)	(2.691)	(0.617)	(0.246)	(0.094)	(1.774)	(0.322)	(0.720)	(0.261)
util_rate_sse	−0.096	−0.066	**−0.029***	−0.008	−0.006	−0.048	−0.013	−0.012	−0.010
	(0.117)	(0.104)	(0.015)	(0.013)	(0.004)	(0.081)	(0.009)	(0.022)	(0.007)
N	335	335	335	335	335	335	335	335	335
R^2	0.701	0.706	0.644	0.571	0.386	0.698	0.619	0.653	0.554

asmt: average summer maximum temperature, *exp_health*: expenditure on health, *pct_urban*: percent urban population, *util_rate_sse*: utilization rate in social sector expenditure, *td_h*: total deaths due to heatstroke, *md_h*: male deaths due to heatstroke, *fd_h*: female deaths due to heatstroke, *md_lt30_h*: deaths due to heatstroke among males below 30 y, *fd_lt30_h*: deaths due to heatstroke among females below 30 y, *md_30_59_h*: deaths due to heatstroke among males between 30–59 y, *fd_30_59_h*: deaths due to heatstroke among females between 30–59 y, *md_60_h*: deaths due to heatstroke among males 60 y and above, *fd_60_h stands*: due to heatstroke among females 60 y and above. Estimated coefficients for each model is based on the full model, which controls for the main variable of interest (*asmt*) and other independent variables (*exp_health*, *pct_urban*, *util_rate_sse*). All models include state and year fixed-effects. Robust standard errors, clustered at the state-level, are within parenthesis.
****p* < 0.01, ***p* < 0.05, **p* < 0.10.

Table 5. Regression result: association between average winter minimum temperature and mortality due to exposure to cold.

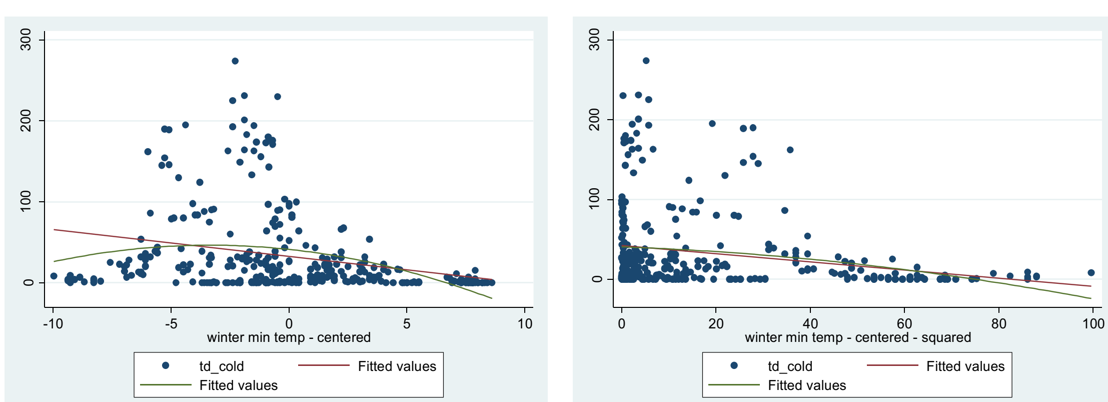
	Dependent variable								
Independent variable	*td_c*	*md_c*	*fd_c*	*md_lt30_c*	*fd_lt30_c*	*md_30_59_c*	*fd_30_59_c*	*md_60_c*	*fd_60_c*
awmt	1.093	0.650	0.443	0.094	0.084	0.045	0.061	0.510	0.299
	(2.614)	(2.325)	(0.480)	(0.363)	(0.140)	(1.846)	(0.212)	(0.372)	(0.251)
exp_health	−6.948	−5.606	−1.342	−0.888	−0.188	−2.966	−0.504	−1.753	−0.649
	(5.165)	(3.720)	(1.587)	(0.524)	(0.331)	(2.118)	(0.706)	(1.402)	(0.579)
pct_urban	−0.688	−0.316	−0.372	−0.079	−0.108	0.202	−0.152	−0.439	−0.112
	(2.076)	(1.743)	(0.443)	(0.191)	(0.098)	(1.227)	(0.195)	(0.484)	(0.174)
util_rate_sse	−0.105	−0.075	−0.029	−0.018	−0.013	−0.020	−0.009	−0.037	−0.008
	(0.119)	(0.095)	(0.029)	(0.014)	(0.009)	(0.061)	(0.011)	(0.027)	(0.013)
N	329	329	329	329	329	329	329	329	329
R^2	0.849	0.850	0.731	0.682	0.554	0.812	0.609	0.871	0.686

awmt: average winter minimum temperature, *exp_health*: expenditure on health, *pct_urban*: percent urban population, *util_rate_sse*: utilization rate in social sector expenditure, *td_c*: total deaths due to exposure to cold, *md_c*: male deaths due to exposure to cold, *fd_c*: female deaths due to exposure to cold, *md_lt30_c*: deaths due to exposure to cold among males below 30 y, *fd_lt30_c*: deaths due to exposure to cold among females below 30 y, *md_30_59_c*: deaths due to exposure to cold among males between 30–59 y, *fd_30_59_c*: deaths due to exposure to cold among females between 30–59 y, *md_60_c*: deaths due to exposure to cold among males 60 y and above, *fd_60_c*: deaths due to exposure to cold among females 60 y and above. Estimated coefficients for each model is based on the full model, which controls for the main variable of interest (*awmt*) and other independent variables (*exp_health*, *pct_urban*, *util_rate_sse*). All models include state and year fixed-effects. Robust standard errors, clustered at the state-level, are within parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.



(a) (b)

Figure 3. Deaths due to heatstroke and: (a) mean-centered average summer maximum temperature (smt_c) and (b) square of smt_c (smt_c_sq).



(a) (b)

Figure 4. Deaths due to exposure to cold and: (a) mean-centered average winter minimum temperature (wmt_c) and (b) square of wmt_c (wmt_c_sq).

Table 6. Regression result: exposure to mean-centered extreme temperature and mortality.

Model 1: Mortality due to heatstroke		Model 2: Mortality due to exposure to cold	
Independent variable	Dependent variable (*td_h*)	Independent variable	Dependent variable (*td_c*)
smt_c	**7.911****	*wmt_c*	0.506
	(3.177)		(2.583)
smt_c_sq	**0.798****	*wmt_c_sq*	−0.213
	(0.309)		(0.240)
exp_health	−1.894	*exp_health*	−7.024
	(2.673)		(5.214)
pct_urban	−2.768	*pct_urban*	−0.704
	(3.094)		(2.075)
util_rate_sse	−0.080	*util_rate_sse*	−0.094
	(0.112)		(0.114)
N	335		329
R^2	0.712		0.849

smt_c: mean-centered average summer maximum temperature, *smt_c_sq*: square of mean-centered average summer maximum temperature, *wmt_c*: mean-centered average winter minimum temperature, *wmt_c_sq*: square of mean-centered average winter minimum temperature, *exp_health*: expenditure on health, *pct_urban*: percent urban population, *util_rate_sse*: utilization rate in social sector expenditure, *td_c*: total deaths due to exposure to cold, *td_h*: total deaths due to heatstroke. Estimated coefficients for each model is based on the full model, which controls for the main variable of interest (*smt_c* and *smt_c_sq* for model 1; *wmt_c* and *wmt_c_sq* for model 2) and other independent variables (*exp_health*, *pct_urban*, *util_rate_sse*). All models include state and year fixed-effects. Robust standard errors, clustered at the state-level, are within parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 7. Regression result: exposure to variable range of average summer maximum temperature and mortality due to heatstroke.

	Dependent variable								
Independent variable	*td_h*	*md_h*	*fd_h*	*md_lt30_h*	*fd_lt30_h*	*md_30_59_h*	*fd_30_59_h*	*md_60_h*	*fd_60_h*
asmt1	−2.115	−2.610	0.495	0.100	**0.305****	−2.324	−0.003	−0.386	0.194
	(3.823)	(3.253)	(0.737)	(0.327)	(0.144)	(2.297)	(0.428)	(0.769)	(0.254)
asmt2	**21.50*****	**18.21*****	**3.292****	**0.991***	0.114	**12.93*****	**1.873****	**4.283****	**1.305***
	(7.518)	(6.284)	(1.417)	(0.534)	(0.221)	(4.375)	(0.884)	(1.628)	(0.653)
asmt_top	−8.959	−6.065	**−2.894****	0.017	−0.211	−5.590	**−2.184***	−0.493	−0.498
	(8.287)	(7.263)	(1.372)	(0.533)	(0.288)	(5.131)	(1.129)	(2.175)	(0.697)
exp_health	−2.176	−1.392	−0.784	−0.431	−0.143	−0.156	−0.306	−0.806	−0.334
	(2.877)	(2.245)	(0.791)	(0.425)	(0.152)	(1.414)	(0.418)	(0.659)	(0.430)
pct_urban	−2.446	−1.427	−1.020	0.010	−0.147	−0.946	−0.547	−0.490	−0.326
	(3.273)	(2.705)	(0.643)	(0.243)	(0.095)	(1.776)	(0.344)	(0.732)	(0.255)
util_rate_sse	−0.0817	−0.053	**−0.028***	−0.007	−0.006	−0.039	−0.013	−0.007	−0.009
	(0.120)	(0.106)	(0.015)	(0.013)	(0.004)	(0.081)	(0.010)	(0.024)	(0.008)
N	335	335	335	335	335	335	335	335	335
R^2	0.716	0.723	0.651	0.575	0.386	0.717	0.630	0.667	0.561

asmt: average summer maximum temperature (here this variable is divided into three temperature bins as *asmt1*: $< 33°C$, *asmt2*: 33–38°*C*, *asmt_top*: $\geq 38°C$), *exp_health*: expenditure on health, *pct_urban*: percent urban population, *util_rate_sse*: utilization rate in social sector expenditure, *td_h*: total deaths due to heatstroke, *md_h*: male deaths due to heatstroke, *fd_h*: female deaths due to heatstroke, *md_lt30_h*: deaths due to heatstroke among males below 30 y, *fd_lt30_h*: deaths due to heatstroke among females below 30 y, *md_30_59_h*: deaths due to heatstroke among males between 30–59 y, *fd_30_59_h*: deaths due to heatstroke among females between 30–59 y, *md_60_h*: deaths due to heatstroke among males 60 y and above, *fd_60_h*: deaths due to heatstroke among females 60 y and above. Estimated coefficients for each model is based on the full model, which controls for the main variable of interest (*asmt1*, *asmt2, and asmt_top*) and other independent variables (*exp_health*, *pct_urban*, *util_rate_sse*). All models include state and year fixed-effects. Robust standard errors, clustered at the state-level, are within parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 8. Regression result: exposure to variable range of average winter minimum temperature and mortality due to exposure to cold.

	Dependent variable								
Independent variable	*td_c*	*md_c*	*fd_c*	*md_lt30_c*	*fd_lt30_c*	*md_30_59_c*	*fd_30_59_c*	*md_60_c*	*fd_60_c*
awmt1	**10.46****	**9.177****	1.280	**1.289*****	0.183	**6.231****	0.450	**1.657***	0.648
	(4.337)	(3.666)	(0.946)	(0.387)	(0.159)	(2.957)	(0.449)	(0.890)	(0.448)
awmt2	**−13.24****	**−12.62****	−0.622	**−1.323****	−0.121	**−10.03****	−0.201	−1.265	−0.299
	(5.882)	(5.458)	(0.952)	(0.538)	(0.145)	(4.701)	(0.305)	(0.748)	(0.662)
awmt3	7.261	7.054	0.206	−0.010	0.0392	6.945	−0.043	0.119	0.210
	(7.124)	(5.695)	(2.130)	(0.923)	(0.357)	(4.212)	(1.091)	(1.485)	(0.959)
awmt_top	−8.357	−5.724	−2.634	−0.063	−0.072	−5.134	−1.283	−0.528	−1.278
	(6.875)	(5.780)	(2.164)	(1.092)	(0.558)	(4.169)	(0.777)	(1.309)	(1.402)
exp_health	−7.148	−5.818	−1.330	**−0.920***	−0.190	−3.120	−0.497	−1.778	−0.643
	(5.273)	(3.777)	(1.632)	(0.536)	(0.341)	(2.136)	(0.725)	(1.429)	(0.594)
pct_urban	−0.611	−0.241	−0.370	−0.081	−0.108	0.279	−0.152	−0.439	−0.110
	(2.109)	(1.759)	(0.465)	(0.198)	(0.102)	(1.220)	(0.205)	(0.499)	(0.180)
util_rate_sse	−0.118	−0.0904	−0.0277	−0.017	−0.013	−0.037	−0.008	−0.036	−0.008
	(0.103)	(0.0836)	(0.0251)	(0.014)	(0.009)	(0.053)	(0.011)	(0.024)	(0.012)
N	329	329	329	329	329	329	329	329	329
R^2	0.851	0.853	0.733	0.684	0.554	0.817	0.611	0.871	0.688

awmt: average winter minimum temperature (here this variable is divided into four temperature bins as, *awmt1*: < 5°*C*, *awmt2*: 5–10°*C*, *awmt3*: 10–15°*C*, *awmt_top*: ≥15°*C*), *exp_health*: expenditure on health, *pct_urban*: percent urban population, *util_rate_sse*: utilization rate in social sector expenditure, *td_c*: total deaths due to exposure to cold, *md_c*: male deaths due to exposure to cold, *fd_c*: female deaths due to exposure to cold, *md_lt30_c*: deaths due to exposure to cold among males below 30 y, *fd_lt30_c*: deaths due to exposure to cold among females below 30 y, *md_30_59_c*: deaths due to exposure to cold among males between 30–59 y, *fd_30_59_c*: deaths due to exposure to cold among females between 30–59 y, *md_60_c*: deaths due to exposure to cold among males 60 y and above, *fd_60_c*: deaths due to exposure to cold among females 60 y and above. Estimated coefficients for each model is based on the full model, which controls for the main variable of interest (*awmt1, awmt2, awmt3, and awmt_top*) and other independent variables (*exp_health*, *pct_urban*, *util_rate_sse*). All models include state and year fixed-effects. Robust standard errors, clustered at the state-level, are within parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

effects (see additional tables in the appendix). This meant that as winter temperature dipped, there were additional deaths, though not statistically significant.

Next, we present the results that are based on two types of analysis that explored whether exposure to different levels of hot and cold temperature differentially impacted mortality due to heatstroke and exposure to cold, respectively. First, panel (a) in Figures 3 and 4 plots the number of deaths due to heatstroke (Figure 3) and exposure to cold (Figure 4) on mean-centered summer maximum and winter minimum temperatures, respectively. Panel (b) in Figures 3 and 4 plots the number of deaths due to heatstroke (Figure 3) and exposure to cold (Figure 4) on their square terms, respectively. Model 1 in Table 6 presents the regression results of total deaths due to heatstroke on the mean-centered average summer maximum temperature and its square factor, along with other covariates. Similarly, Model 2 in Table 6 presents the regression result of exposure to cold. The regression coefficient for the squared term was of importance. As exposure to heatstroke increased by one-degree Celsius, mortality also significantly increased ($p < 0.05$), though at a smaller rate. On the other hand, the negative coefficient for *wmt_c_sq* indicated that as temperature is reduced by one-degree Celsius, mortality increases, though insignificantly.

Second, Tables 7 and 8 present the piecewise regression results when mortality due to heatstroke and exposure to cold was separately regressed on the temperature categories generated from *asmt* and *awmt*, respectively.

The average summer maximum temperature (*asmt*) ranged between 24.8°*C* and 41.4°*C* (see Table 1). Table 7 demonstrates that with a one-degree Celsius increase in average summer maximum temperature of up to 33°*C*, there were around two less total deaths and far fewer male deaths compared to female deaths, albeit all statistically insignificant (coefficients for *asmt1*). However, women below 30 y were more vulnerable to any increase in temperature up to 33°*C*; almost three out of every 10 women died in this age group ($p < 0.05$). Citizens, however, are more vulnerable to a one-degree increase in the average summer maximum temperature in the range of 33–38°*C* (coefficients for *asmt2*). As the average summer maximum temperature increased by one-degree Celsius, there were 21 additional total deaths ($p < 0.01$), with more male deaths across all age groups. In terms of total deaths and those in the age-group of 30–59 y, males ($p < 0.01$) were around six times more susceptible than females ($p < 0.05$). Increase in average summer maximum temperature by one-degree Celsius above 38°*C* (coefficients for *asmt_top*) had less impact on mortality, notably around three fewer total female deaths ($p < 0.05$) and two less deaths among females in the age-group of 30–59 y ($p < 0.10$).

Average winter minimum temperature (*awmt*) during the study period ranged between 1.6°*C* and 20.2°*C* (see Table 1). Table 8 shows that when the average winter minimum temperature, up to 5°*C*, dipped by one-degree Celsius there were around 10 fewer deaths ($p < 0.05$), far fewer total male deaths compared to the total number of female deaths (around nine males versus one female, $p < 0.05$), as well as fewer male deaths across various age groups (coefficients for *awmt1*). However, when the average winter minimum temperature in the range of 5–10°*C* lowered by one-degree Celsius, there were 13 additional total deaths ($p < 0.05$), with males 21 times more susceptible compared to females ($p < 0.05$). The male population was more vulnerable to the temperature drop across various age groups. As temperature in the range of 5–10°*C* dropped by one-degree Celsius, there were 11 times more deaths among males in the below 30 y age group ($p < 0.05$) and almost 50 times more deaths in 30–59 y category ($p < 0.05$). As temperature dipped by one-degree Celsius, above 15°*C*, there were more deaths across the population, however this was not statistically significant.

Discussion

Our study showed five salient findings. Our findings showed that the average summer maximum

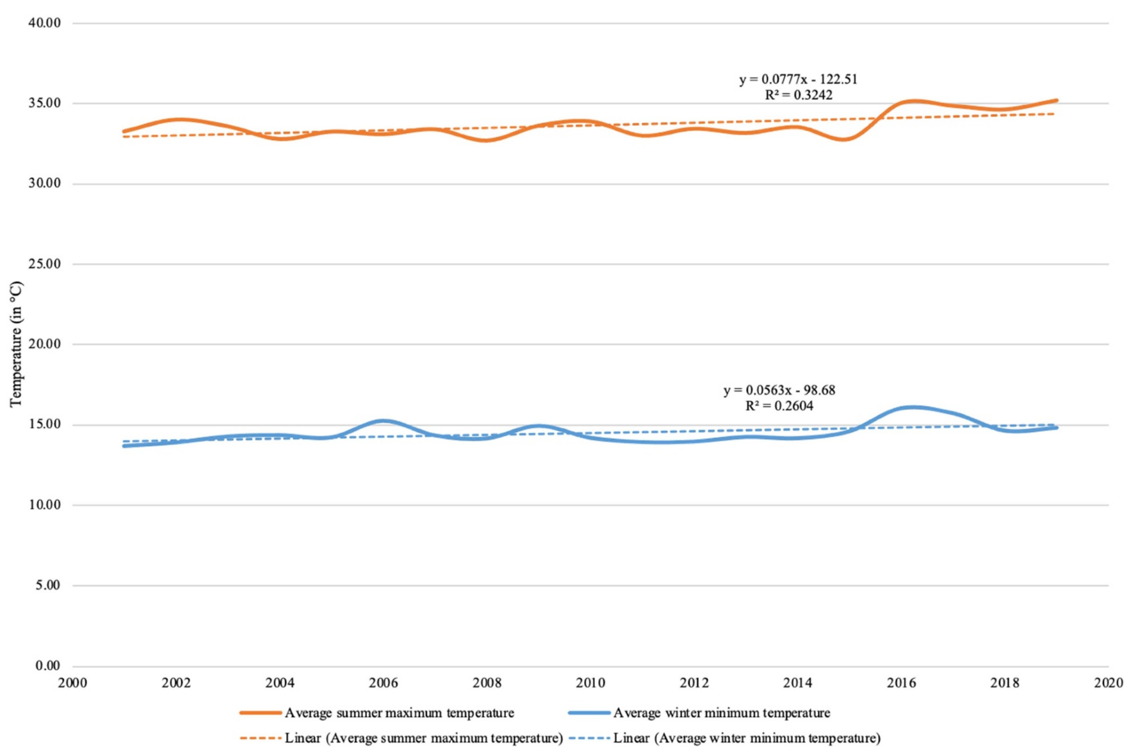


Figure 5. Average summer maximum and winter minimum temperature in India, 2001–2019.
Source: Authors' computation using IMD data.

and the average winter minimum temperature in India were on the rise (Figure 5). This translates to an overall increase in the average annual temperature in India [41], which follows the global pattern of an overall increase in average temperature, mostly due to climate change [42]. Linear trend in mortality due to heatstroke and cold exposure indicated an overall increase in mortality in India from 2001 to 2019 (Figure 1, panel (a): a linear trend as represented by dashed lines), albeit a decrease in absolute terms compared to 2015. India experienced disastrous heatwaves and cold waves in 2015, leading to the greatest number of deaths in a calendar year due to extreme temperature [43]. After 2015, while mortality has decreased, it continued to increase for cold exposure (since 2016–2019), whereas for heatstroke, it registered an increase after 2018. Our findings converged with existing evidence on mortality due to exposure to extreme heat, likely to cause heatstroke, both within and outside of India [44–47], while we note some differences with existing work on mortality due to exposure to cold [44]. Given India's geographical stretch and its variation in extreme temperatures, these heterogeneities need to be accounted for in national and state-level mitigation efforts.

Study findings also signify the importance of exploring the effect of varying degrees of hot and cold temperature ranges on mortality. This is contrary to a common pitfall, which scholars have suggested to avoid, that of extrapolating mortality results across different temperatures, such as from extreme heat to mild temperature [6]. Piecewise regression analysis indicated that mortality may not always be the highest in the most severe temperature-type categories, i.e. extreme cold ($<5^\circ C$) and extreme hot ($\geq 38^\circ C$). This could be because residents from areas that normally experience the most extreme temperatures may have their own adaptive mechanisms [48–50]. Our findings indicate that most deaths were reported from less severe summer ($33–38^\circ C$) and winter ($5–10^\circ C$) temperature bins. These deaths were mostly reported from states, including some economically poorer ones such as Bihar, Jharkhand, and Uttar Pradesh, which over time have not experienced extreme temperatures and are experiencing a shift from normal temperatures in recent study years. As such, these states will likely have lower adaptation and mitigation strategies in place. Our findings therefore highlight the importance of shifting the focus to these states to implement temperature-sensitive plans to control such preventable mortality.

Second, as expected, we found state-level heterogeneity in the number of deaths due to heatstroke and exposure to cold. Between 2000 and 2014, the top-five states accounting for the greatest number of deaths due to heatstroke, were Andhra Pradesh, Uttar Pradesh, Punjab, Odisha, and West Bengal (Table 2). Similarly, the top-five states that registered the greatest number of deaths due to exposure to cold were Uttar Pradesh, Punjab, Bihar, Haryana, and Jharkhand (Table 3). While we recognize that this pattern could be due to state-level differences in registration systems and mortality data collection, our findings demonstrate the need to urgently develop state-focused strategies to reduce such preventable mortality. For example, the Ahmedabad Heat Action Plan (HAP), which was implemented in 2013 in Gujarat state, was associated with a decrease in all-cause mortality in subsequent years [51]. This success has resulted in the implementation of HAPs across 23 states in the country [52], as well as at several district- and city-levels [53]. However, most HAPs have failed to effectively integrate vulnerability assessment, socio-economic factors, and hotspot identification while developing mitigation and adaptation strategies [53]. Strengthening these plans and identifying key issues in implementing them on the ground will be important local actionable steps to avert mortality. In addition, we need to further assess via granular data the sociodemographic characteristics of those affected by this mortality, to understand the scope of vulnerability and the kind of social support programs that are required.

Furthermore, the existing local heat action plans may need to be assessed for scale-up at the state level, and inter-state learning on what works is critical to enable a rapid response. While there has been some response to exposure to extreme heat, response to cold exposure requires welfare measures in the form of night shelters and alternative energy sources. Night shelters, in particular, have been an important state response to prevent deaths from exposure to extreme cold, especially among poor women, children, and the homeless, but the safety and quality of these can be a concern [54]. In the recent years, several states reeling under cold waves, such as Punjab, Delhi, Uttar Pradesh, and Bihar, have taken measures such as increased the number of night shelters and/or improved the existing conditions to provide better living conditions for the homeless people [55–58]. Further, while heat and cold exposure are seemingly "natural" causes of death, considering built environment interventions such as shaded walkways, covered bus stops, and enhancing availability of water and sanitation facilities can prevent loss of life and enable health and wellbeing among populations that are affected the most [59].

Third, we found that men in general, and particularly those in the working age group of 30–59 y, were more vulnerable to heat-related mortality. While this finding resonates with another study from India [60], global evidence mostly suggests that women are more vulnerable to extreme heat and occupational heat stress [61–65]. As more men compared to women in India work outdoors [66], men, compared to women, may be more vulnerable to heat due to their engagement in livelihood-generating activities, even at the peak of summer [67,68]. This finding should be examined from two perspectives. One, it shows the need to consider economic measures and income support programs for households during extreme temperatures and heat/cold waves. This may be particularly relevant for low-income populations and daily wage workers who may feel compelled by their economic circumstances to engage in outdoor-livelihood activities despite known risks, as suggested elsewhere [64]. Efforts should also be made to raise both societal- and individual-level awareness about the risks of heat exposure to ensure effective risk adaptation and mitigation strategies. Societal-level awareness could be adapted from HAP [21], whereas individual-level strategies could include self-pacing at work, drinking adequate water, taking rest break, and wearing ventilated garments [64]. Two, there should be adequate checks put in place to determine any bias in reporting deaths among women due to extreme heat, particularly when evidence suggests them to be vulnerable [69].

Fourth, we found that with an increase in health expenditure, mortality due to heatstroke declined, and there was some evidence of the same for cold exposure. Health and social expenditure represent state capacity, commitment, and action, and indicate state preparedness and a pro-active approach toward ensuring the health and wellbeing of populations. We also found that heat-related mortality decreased with increase in urban residents. Urban residence and expenditure on health and social systems may be proxies for availability and accessibility to health care, representing the scope for faster medical care, which is a critical factor for those suffering from heat stress [70].

Finally, while, expectedly, exposure to heat had a greater association with mortality, we found similar patterns with reduced effect estimates for cold exposure mortality. As discussed above, cold exposure interventions may include accessibility to night shelters, income support programs, and even diet-support interventions [54]. India's Supreme Court and several high courts have requested data to understand the state of these night shelters; these interventions are much needed to push states into providing supportive interventions for the most vulnerable during the harshest of weathers [54]. Qualitative research is needed to understand the available services in these shelters and how quality and safety in these spaces may be improved.

We believe, this is one of the first comprehensive assessments from India that has studied the time trends as well as the association between exposure to extreme summer and winter temperatures and mortality due to heatstroke and cold exposure, respectively, using panel data. In this study, we were able to provide state-level estimates by gender and age to test this association using linear and non-linear estimations, which have important policy implications.

Our findings need to be considered in light of the following limitations. First, as mortality estimates are sourced from police records, there is a possibility that not all deaths are reported and recorded. Death registration in the country suffers from incompleteness [30,31]. As such, our findings should be considered with some degree of conservativeness. Our findings, though, could serve as a reference point for future studies in this direction. Second, we understand that this association is ecological in nature, and since our data come from criminal records and not hospital data, we are unable to test for the role of any mediating factors, such as individual health-related vulnerabilities, that may have led to death from heatstroke or cold exposure. We recommend that hospital-based studies be conducted in the future that may be able to better examine the pathways to risk from extreme heat or cold exposure. Third, we did not have data on policy characteristics such as the number of shelters or personal characteristics such as education or wealth to understand trends by socioeconomic status. This can also provide insight into who is at greater risk within these states. Finally, limited data were available between 2001 and 2014, and beyond 2014, we did not have disaggregated data by gender and age at the state-level to conduct the same analyses. To understand the risks of climate change in a more comprehensive way, there is a need to understand and expand the data eco-systems to include both micro and macro studies to understand climate-related risks and their impacts on health and well-being. For instance, there is a need to understand the links between extreme temperature changes, and their associations with livelihoods, health, and well-being. Our analysis captures extreme outcomes and mortality; however, there is scope to consider several other important and impactful health and development outcomes along the way.

Conclusions

This study provides empirical evidence to understand the association between extreme temperatures and mortality between 2001 and 2019. We found a large burden of excess deaths due to heatstroke and cold exposure. Working age men were more susceptible to mortality from heat exposure, showing the need for strengthening warning systems and livelihood interventions to avert these deaths. The association between extreme cold temperature and mortality was not significant. Findings point toward the need to identify hotspots for heat and cold exposure deaths and to implement a framework for designing sustainable policies that can enable resilience among populations.

Notes

1. The 24 states included in our analysis, in alphabetical order, are: Andhra Pradesh (includes the newly formed state of Telangana in 2014), Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Delhi, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir (pre-2019), Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Meghalaya, Odisha, Punjab, Rajasthan, Tamil Nadu, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal.
2. For the first break, any change of more than 2% in the growth rate (up or down) is considered to be a genuine break. If the first up-break follows a down-break, then the absolute magnitude of the growth difference must be 3% and vice versa. And, if, however, the first up-break follows an up-break then a change of only 1% (in absolute value) qualifies as a genuine break and similar for down-breaks.

Abbreviations

ADSI	Accidental Deaths and Suicides in India
HAP	Heat Action Plan
IMD	India Meteorological Department
LMICs	Low- and Middle-Income Countries
NCRB	National Crime Records Bureau
RBI	Reserve Bank of India
SCRB	State Crime Records Bureau
WHO	World Health Organization

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Ethics approval and consent to participate

Mortality data are aggregated at the state-level, and hence, there is no identifiable individual-level personal information. We used these data from secondary sources that are available for public use. The study was approved by the Research and Ethics Review Board at JGU.

Availability of data and materials

Mortality data are publicly available from the NCRB website (https://ncrb.gov.in/accidental-deaths-suicides-in-india-adsi.html). Data on health expenditure and other social-sector expenditures are publicly available from the RBI website (https://rbi.org.in/Scripts/AnnualPublications.aspx?head=State%20Finances%20:%20A%20Study%20of%20Budgets).
The temperature dataset used in this study is not publicly available because we are not the creator of the dataset, but it is available from IMD Pune on reasonable request (https://www.imdpune.gov.in).

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