

# Excess Mortality Risk Due to Heat Stress in Different Climatic Zones of India

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ACCESS	III Metrics & More	E Article	Recomm	endations	S) S	Supporting I	Information	n
ABSTRACT: Indi	ia is at a high risk of heat st	ress-induced health	F	Chennai	De	lhi	Varanas	si
	omic losses owing to its tro		Age:>64y-	5.7(2.1,9.4)	-	4.2(3.3,5.1)	-	7.5(5.5,9.6)
	, and inadequate adaptive p		Age:45-64y	1.4(-2.8,5.6)	+	2.3(1.5,3.2)		7.7(5.0,10.3)
		e	Age:19-44y	1.6(-2.8,6.0)	+	2.5(1.4,3.7)		4.6(1.3,7.8)
impacts of heat stress across climate zones in India have not been				• 0.9(-5.6,7.3)	-	2.6(0.7,4.5)		3.2(-2.2,8.5)

infjacts of heat stress across clinic zones in findia have not been adequately explored. Here, we examine and report the vulnerability to heat stress in India using 42 years (1979–2020) of meteorological data from ERA-5 and developed climate-zonespecific percentile-based human comfort class thresholds. We found that the heat stress is usually 1–4 °C higher on heatwave (HW) days than on nonheatwave (NHW) days. However, the stress on NHW days remains considerable and cannot be neglected. We then showed the association of a newly formulated India heat index (IHI) with daily all-cause mortality in three cities – Delhi

	Chennai	Delhi		Varanas	i		
Age:>64y	5.7(2.1,9.4)	-	4.2(3.3,5.1)		7.5(5.5,9.6)		
Age:45-64y	• 1.4(-2.8,5.6)	+	2.3(1.5,3.2)		7.7(5.0,10.3)		
Age:19-44y	1.6(-2.8,6.0)	-	2.5(1.4,3.7)		4.6(1.3,7.8)		
Age<19y	0.9(-5.6,7.3)	-	2.6(0.7,4.5)		3.2(-2.2,8.5)		
Female	5.3(1.6,9.1)	+	3.7(2.9,4.6)		6.9(4.6,9.3)		
Male	1.5(-1.6,4.7)	+	2.9(2.2,3.6)	-	6.7(4.8,8.6)		
Heatwave			5.2(3.1,7.3)		6.9(3.8,10.0)		
NonHeatwave		•	1.4(0.6,2.2)	-	3.3(1.2,5.4)		
Sweltering	• 8.0(1.7,14.2)	-	5.9(4.6,7.2)		8.1(6.0,10.3)		
VeryHot	1.0(-4.4,6.5)		3.4(1.1,5.7)		-6.3(-1.9,14.5)		
All	3.1(0.4,5.9)	+	3.2(2.6,3.9)	-	6.8(5.2,8.3)		
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Article

(semiarid), Varanasi (humid subtropical), and Chennai (tropical wet and dry), using a semiparametric quasi-Poisson regression model, adjusted for nonlinear confounding effects of time and  $PM_{2.5}$ . The all-cause mortality risk was enhanced by 8.1% (95% confidence interval, CI: 6.0–10.3), 5.9% (4.6–7.2), and 8.0% (1.7–14.2) during "sweltering" days in Varanasi, Delhi, and Chennai, respectively, relative to "comfortable" days. Across four age groups, the impact was more severe in Varanasi (ranging from a 3.2 to 7.5% increase in mortality risk for a unit rise in IHI) than in Delhi (2.6–4.2% higher risk) and Chennai (0.9–5.7% higher risk). We observed a 3–6 days lag effect of heat stress on mortality in these cities. Our results reveal heterogeneity in heat stress impact across diverse climate zones in India and call for developing an early warning system keeping in mind these regional variations.

KEYWORDS: heatwave, heat stress, relative risk, mortality, India Heat Index, human comfort

## 1. INTRODUCTION

Increasing temperature and changes in moisture content are the prominent mechanisms by which climate change directly impacts the human population.<sup>1</sup> Exposure to high air temperature was associated with increased morbidity and mortality.<sup>1,2</sup> Globally, heat-related deaths account for 0.91% (95% uncertainty interval, UI: 0.56-1.36) of total deaths.<sup>3</sup> Acute heat exposure has been established as a new risk factor in the Global Burden of Disease study.<sup>4</sup> Heat exposure already leads to labor loss of approximately 200 billion hours for those engaged in heavy labor in agriculture and construction.<sup>5</sup> However, the majority of health impact research is focused on high-income countries in the world. Although heat exposure has the most severe impacts on vulnerable populations, limited studies have reported its impacts in low- and middle-income countries (LMICs). Moreover, LMICs like India and countries in Africa, with tropical climates, poor cooling infrastructure, low adaptive capacity, and high population exposure ratios, are reckoned as the most susceptible to dangerous heat and humidity combinations. Such countries have a marginalized capacity to adapt to adverse impacts of climate change and are at higher risk of mortality to increased temperature. $^{6-8}$ 

India is highly vulnerable to the rising frequency of heatwaves<sup>9–11</sup> Heat is one of the leading natural causes of mortality in India, contributing to about 18.2% of deaths.<sup>12</sup> The heat-related mortality increased<sup>13,14</sup> by 146% in India between 1967 and 2009. The May 2010 heatwave (HW) resulted in almost a 43.1% rise in all-cause mortality in Ahmedabad,<sup>7,15</sup> with a 20% increase in all-cause mortality when the temperature rose beyond 40 °C in Surat (2014–2015). A study in Varanasi found a strong association between ambient temperature and mortality, with a 5.61% rise in all-cause mortality with each unit increase in mean temperature in the summer months.<sup>16</sup> Few

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Table 1. Climate-Zone-Specific IHI	(in	°C)	Comfort	Class	Thres	holds	in Indi	ia
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human comfort class thresholds based on IHI								
	climate zones							
comfort classes	arid	semiarid	humid subtropical	tropical wet	tropical wet and dry			
comfortable (≤25th)	22.9	23.0	22.5	23.5	23.8			
warm (>25th to $\leq$ 50th)	22.9-26	23-25.5	22.5-25.4	23.5-25.1	23.8-25.8			
hot (>50th to $\leq$ 75th)	26-28.8	25.5-28	25.4-27.7	25.1-26.7	25.8-28.1			
very hot (>75th to $\leq$ 90th)	28.8-31.4	28-30.5	27.7-30.2	26.7-28.5	28.1-30.5			
sweltering (>90th)	>31.4	>30.5	>30.2	>28.5	>30.5			



Figure 1. Regression statistics of 24-h averaged temperature and relative humidity derived from ERA-5 and ground measurements in the three cities on a daily scale.

studies also highlighted regional, socioeconomic, and demographic variations in heat-related deaths.<sup>7,17,18</sup>

A large share of the existing studies is restricted to solely quantifying the health effects considering only the temperature extremes and not accounting for the contrasting effect of humidity, wind speed, and intensity of solar radiation on human health.<sup>8,11,14,19,20</sup> Some of the indices such as "Heat Index" (HI), "Universal Thermal Comfort Index" (UTCI), "Humidex"<sup>21</sup> or "simplified Wet Bulb Globe Temperature" (sWBGT)<sup>21</sup> developed and used by the Australian Bureau of Meteorology (ABM) use only temperature and relative humidity (RH) to quantify the heat-stress condition. However, it is found that wind and solar radiation also have a direct effect on heat stress conditions, and ignoring these two factors may underestimate or overestimate the heat stress condition.<sup>22-24</sup> RH plays an important role in modulating human discomfort with heat, and under hot and humid conditions, evaporative cooling via sweating tends to be less efficient. In some cases, the sweat rate may exceed the level that is required to maintain a heat balance by evaporative cooling. As a result, the human body not only fails to maintain a stable core temperature but also loses body water via dripping sweat and faces dehydration. High wind speed can partially counter the effect. Therefore, true "heat stress" that impacts human health should include these critical weather variables.<sup>25,20</sup>

The estimates of the level of heat stress and physiological response of the body are still being refined.<sup>27–29</sup> This has been primarily due to challenges in accurately estimating the heat stress, which can vary with behavioral and other adaptive

conditions, as well as due to variations in climate and geography.<sup>27</sup> With climate change, heat stress is projected to intensify throughout the 21st century. However, the current heat indices are all tailored to temperate climate conditions in developed nations.<sup>29,30</sup> A handful of studies estimated the effects of heat stress in India but remained restricted to selected occupational groups like brick workers, agriculture and industrial labor, and its associated economic losses.<sup>31–35</sup>

The diversity in climate conditions, modulated by local geographical factors and diverse seasonality, presents a major challenge for any comprehensive heat stress study in India. A comparative study of existing heat indices<sup>36</sup> proposed localization and modification in WBGT to best capture Indian climatic conditions. Moreover, the globe temperature and natural wet bulb temperature (used to calculate WBGT) are not routinely measured at weather stations and are also not simulated by models. Hence, it is difficult to project heat stress conditions based on the existing relationships of the globe temperature in view of the environmental conditions, thereby limiting their applicability. Dey et al.<sup>37</sup> modified the WBGT to improve the applicability of the index for the Indian climate condition, particularly in terms of common meteorological variables. Further, they proposed climate-zone-specific percentile-based human comfort class thresholds in the absence of any India-specific health studies. Here, we used this modified WBGT and applied the percentile-based thresholds to examine the excess health risks in three major cities, each representing a major climate zone.



India: climate zones and cities

Figure 2. Climate zones of India and the three cities considered in this study.

#### 2. MATERIAL AND METHODS

**2.1. Heat Stress.** As a measure of heat stress, we coined the term India Heat Index (IHI), a modified version of WBGT<sup>37</sup> that can be represented as

IHI = 
$$0.820 \times T_a + 0.123 \times RH + 0.004 \times SR$$
  
-  $0.117 \times WS - 6.727$  (1)

where  $T_a$  is the air temperature normally measured at 2 m above the ground, RH is the relative humidity, SR is the surface radiation, and WS is the wind speed. The relationship was developed by regressing WBGT calculated at point locations proposed by Lemke and Kjellstrom<sup>24</sup> based on a range of  $T_a$  $(20-49.5 \,^{\circ}C)$ , RH (10-100%), WS  $(0.1-20 \, {\rm ms}^{-1})$ , and SR (up to 1050 Wm<sup>2-</sup>) that are usually observed in India across the six climate zones. The correlation between IHI estimated using the regression equation and WBGT calculated following Lemke and Kjellstrom is 0.98 (p < 0.01) along with the normalized rootmean-square error (NRMSE) of 3.1%.

We processed meteorological data from the fifth Generation Atmospheric Reanalysis by the European Center for Medium-Range Weather Forecasts (ERA-5), available at  $0.25^{\circ} \times 0.25^{\circ}$  resolution at every 3-h interval from 1979 to  $2020^{38}$  to estimate IHI. Here, we derived percentile-based climate-zone-specific comfort class thresholds (Table 1) following Dey et al.<sup>37</sup> in absence of any cohort study in the Indian condition. The IHI formula is developed with the range of environmental parameters as per the limits; temperature 20–49.5 °C, humidity 10–100%, wind speed 0.1–20 m/s, solar radiation 0–1050 W/m<sup>2</sup>.

The use of satellite and reanalysis data for monitoring weather conditions and climate change has become increasingly important in recent years. However, it is crucial to ensure that such data are accurate and reliable before using them for research or decision-making. Hence, we first validated the ERA-5 temperature and RH against ground measurements from the network of the Central Pollution Control Board (CPCB) for three cities in India for the past decade (Figure 1). At these stations, temperature and RH are routinely measured by automatic weather stations, and the data are archived and disseminated through the portal cpcb.nic.in. Our analysis shows a high correlation ( $R^2 = 0.86$  and 0.70) and root-mean-square error (RMSE) of 1.82 and 12.3% for temperature and RH, respectively, on a daily scale. Since the IHI is mostly governed by variations in temperature and RH, the robust comparison gave us confidence in the accuracy and reliability of the ERA-5 data in computing heat stress. Besides this, ERA-5 meteorological data are evaluated extensively on a global scale.

Based on 42 years of statistics, we classified human comfort class thresholds separately for the five major climate zones of India (Figure 2), where heat stress is felt (Table 1). We only analyzed meteorological data for the period 16th March to 15th July each year when the stress remains considerable.<sup>37</sup> "Sweltering" days are considered when IHI exceeds 90th percentile values in that region, while the days with IHI in between the 75th to 90th percentiles were classified as "very hot" days. The "hot" and "warm" days were marked for the IHI varying in the 50th to 75th percentile and 25th to 50th percentile ranges, respectively. Only on the days when IHI was below the 25th percentile value we called it "comfortable." The meteorological data for the montane climate zone (the highlands in the northern part of India, shown in Figure 2) has not been processed as earlier studies suggested minimal health risk due to heat stress in that climate zone.<sup>37</sup> The overall



Figure 3. Proportions of IHI comfort class threshold days in the three cities for NHW days in summer.

frequency distributions of the IHI in the three cities are shown in Figure S1.

We separated the HW and NHW days following the criteria of the Indian Meteorological Department (IMD). For the plains covering arid, semiarid, humid subtropical, and tropical wet and dry climate zones, HW days were considered when the maximum temperature exceeded 40 °C for 2 consecutive days. For the coastal regions covering the tropical wet climate zone, days with temperatures above 37 °C were considered to be HW days. We estimated the IHI statistics separately for each climate zone to examine the changes in stress on HW days relative to NHW days during our study period.

2.2. All-Cause Nontrauma Mortality Data in Study Locations. We analyzed the daily all-cause nontrauma mortality data for three cities, Delhi, Varanasi, and Chennai (Figure 2). Delhi is the capital city of India and a metropolitan city spread over 1484 km<sup>2</sup> area and home to more than 20 million population.<sup>39</sup> The climate is semiarid, and it has long summer and winter. Chennai is a megacity located in the southern state of Tamil Nadu. It is a coastal city with a geographical area of  $426 \text{ km}^2$  and a home to more than 5 million population. Though this city rarely faces heatwave conditions, the hot and humid conditions are prevalent due to its tropical and coastal location. Varanasi is located in the central part of the Indo-Gangetic Basin and lies on the bank of the river Ganga. The city is home to more than 1.2 million people with a geographical area of less than 100 km<sup>2</sup>. The climate of Varanasi is humid and subtropical, with high temperatures in summer leading to heatwave conditions.

Since these three cities belong to three different climate zones, semiarid, humid subtropical, and tropical wet and dry climate zones (see Figure 2), it allowed us to compare the contrast in heat stress and its impacts across different climate zones. We also noted that these three climate zones cover more than 75% of the area and are inhabited by around 88% population in India.

The mortality records in each city were collected and archived by the municipal corporations. We used the data from January 1, 2013, to September 29, 2017, for Delhi; January 1, 2009, to October 7, 2016, for Varanasi; and January 1, 2004, to September 30, 2009, for Chennai. Accidental deaths due to trauma like accidents, fires, and suicides were excluded from the daily counts to obtain all-cause nontrauma mortality. Earlier, these mortality data sets were utilized to understand the impact of acute exposure to air pollution in Delhi,<sup>40</sup> Varanasi,<sup>41</sup> and Chennai.<sup>32</sup>

**2.3. Ambient PM**<sub>2.5</sub> **Data.** We analyzed the satellite-based  $PM_{2.5}$  exposure data set,<sup>42</sup> derived from satellite-retrieved aerosol optical depth (AOD) at 1 km × 1 km resolution on a daily time scale. The algorithm was standardized for India, where surface  $PM_{2.5}$  was estimated by converting Multiangle

Implementation of Atmospheric Correction AOD using spatially and temporally varying scaling factors (i.e., the ratio of  $PM_{2.5}/AOD$ ). The satellite-derived data showed daily  $R^2$  and root-mean-square error of 0.89 and 10.54  $\mu$ g m<sup>-3</sup> in Chennai, 0.96 and 15.52  $\mu$ g m<sup>-3</sup> in Delhi, and 0.95 and 12.14  $\mu$ g m<sup>-3</sup> in Varanasi, respectively, against ground-based monitoring stations maintained by the CPCB of India (Figure S2). Satellite-PM<sub>2.5</sub> was used in place of ground monitoring data because the ground monitoring data was not available consistently for the duration we have all-cause mortality data. Moreover, the number of monitoring sites was inadequate for a robust representation of the cities during our study period.

**2.4. Statistical Modeling.** We used the semiparametric quasi-Poisson generalized additive regression model to estimate the acute effects of heat stress exposure on daily all-cause nontrauma mortality, adjusting for potential nonlinear confounders such as time trends and ambient  $PM_{2.5}$  exposure in the three cities separately. For the modeling analysis, we extracted daily IHI and  $PM_{2.5}$  statistics for the cities from the grids lying within the city boundaries in a GIS environment.

The regression model can be represented as

$$log(E\{(mortality)_t\}) = \alpha + \beta_1(IHI)_t + f_1(time)_t + \gamma(PM_{2.5})_t$$
(2)

where  $\beta_1$  is the regression coefficients or slopes estimated with respect to the IHI exposure metric over time.  $f_1$  is the smoothed function (penalized cubic smoothing spline) of nonlinear confounding factor of time and  $\gamma$  is a coefficient of the linear confounding factor of ambient PM<sub>2.5</sub> level. We used statistical software R version 4.2.1 for the entire analysis.

We considered three exposure metrics to understand the overall impact of heat stress in these three cities, representing three contrasting climate zones. First, we estimated the acute impacts of heat stress on all-cause mortality for different comfort class thresholds (determined from the IHI values). Second, we estimated the differences in the health impacts on HW days vs NHW days. We stratified our analyses for gender and different age groups in each city. Third, we finally examined the response of mortality to IHI by the generalized additive model with quasi-Poisson family after adjusting for time trend and PM<sub>2.5</sub> exposure (allowing IHI to be cubic penalized spline function) and validated percentile-based IHI classifications mentioned above against change in slopes across the range of IHI. The slopes of the smoothed curve were derived empirically by the definition of slope between two coordinates. This allowed us to estimate the excess mortality risks at various comfort class thresholds (that we define statistically) in each climate zone relative to the comfortable conditions as the conditions worsen.

#### 3. RESULTS

**3.1. Descriptive Statistics.** In Delhi, the mean temperature during the summer between 2013 and 2017 was 30.4 °C, whereas the IHI was 29.5 °C. The average ambient PM<sub>2.5</sub> exposure during the study period was 78.2  $\mu$ g m<sup>-3</sup>. The average number of deaths during the study period was 181. In Varanasi, the mean temperature during the study period was 30.9 °C, whereas that of IHI was 29.6 °C. The PM<sub>2.5</sub> exposure in Varanasi in 2009–2016 was 56.6  $\mu$ g m<sup>-3</sup>, and average daily deaths were 21, much lower than those in Delhi. In Chennai, the mean temperature during the study period of 2004–2009 was 30.4 °C and IHI 30.3 °C. The average daily mortality in Chennai was 103 with PM<sub>2.5</sub> exposure at 67.4  $\mu$ g m<sup>-3</sup>. Table S1 provides a summary of all input variables in the model for the three cities.

The relative proportions of IHI comfort classes under NHW conditions for the three representative cities are shown in Figure 3. Sweltering conditions prevailed all the time on HW days in all three cities. 41, 54, and 45% of NHW days are categorized as sweltering conditions in Delhi, Varanasi, and Chennai, respectively. During the study period, Delhi had only 3% comfortable days, even on NHW days, while in the other two cities, comfortable days were not present at all. Chennai (51%) had a larger share of very hot days than Varanasi (31%) and Delhi (30%) in NHW conditions. 17% of days in Delhi were hot, while the corresponding numbers for Varanasi and Chennai were 12 and 4%, respectively.

**3.2. Heat Stress during the HW and NHW Days.** Figure 4 shows the box plots of IHI during the HW and NHW days in the



Figure 4. IHI (in  $^{\circ}$ C) during the heatwave (orange boxes) and nonheatwave (green boxes) days in five climate zones of India. The horizontal red lines and dashes indicate the "sweltering" and "very-hot" thresholds. Error bars indicate the 5th–95th percentile ranges.

five major climate zones of India in the last 4 decades. The maximum difference (of 4.5 °C by median values) was found for the arid climate zone, while the lowest difference ( $\sim$ 1.5 °C) was found for the tropical wet climate zone. The arid climate zone experienced HWs for 71.2% of total summer days (16th March to 15th July) in the last 4 decades. The corresponding numbers in the semiarid, humid subtropical, tropical wet, and tropical wet and dry zones were 74.2, 56.2, 57.0, and 59.2%, respectively. Among the three cities, Chennai (tropical wet and dry) experienced heatwaves only in 0.2% of the summer days, while Delhi (semiarid) and Varanasi (humid subtropical) experienced heatwaves in 21.0 and 23.0% of the summer days.

Two features are prominent in this figure. First, the comfort class was sweltering on all HW days across the climate zones, indicating additional physiological stress on those days. Second, the heat stress on the NHW days was considerable. In fact, most of the NHW days in semiarid, humid subtropical, tropical wet, and tropical wet and dry were sweltering. Only in the arid climate zone most of the NHW days were below the sweltering threshold.

The climate zones have varied temperatures, RH values, and wind profiles. During the summer, the average temperature was 32.3, 30.8, 29.8, 26.6, 30.4 °C, and RH was 39.7, 48.5, 55, 78.3, and 57.1%, respectively, for the arid, semiarid, humid subtropical, tropical wet, and tropical wet and dry zones. The average wind speed varied in the range of  $2.5-3.1 \text{ m s}^{-1}$  in all four climate zones except arid, where it was 4.4 m s<sup>-1</sup>. The average temperature during HW days was higher by 5.7, 4.1, and 3.3 °C than NHW days in Delhi, Varanasi, and Chennai, respectively. The average wind speed was also found to be higher by  $0.3-0.5 \text{ m s}^{-1}$  in all three cities on HW days. However, the average RH in three cities was lower on HW days. Delhi, Varanasi, and Chennai have 32.2, 42.5, and 58.1% of RH, and the corresponding values for nonheatwave days are 51.8, 52.5, and 72.3%, respectively. High RH is the primary driver of the stress on NHW days in these climate zones. The range for IHI during summer varies between 15 to 39 °C. In our analysis, the maximum IHI values we recorded from different climate zones were 38.7, 37.7, 37.0, 34, 37, and 35 °C, respectively, for arid, semiarid, humid subtropical, tropical wet, tropical wet, and dry climate zones, respectively, over last the 42 years.

3.3. Impact of Heat Stress on Mortality. We estimated a 3.1% (95% confidence interval, CI: 0.4–5.9) increase in daily allcause nontrauma mortality in Chennai, 3.2% (2.6-3.9) in Delhi, and 6.8% (5.2–8.3) in Varanasi for every unit increase in IHI (Figure 5). The highest effect was observed during the sweltering days (8% increase in Chennai, 5.9% in Delhi, and 8.1% in Varanasi for every unit increase in IHI). For the next lower comfort class, "very hot", the effect was drastically reduced to a 1% increase in mortality per unit increase in IHI in Chennai. In Delhi (3.4% increase in mortality) and Varanasi (6.4% increase in mortality), the reduction in risks is more moderate. The excess mortality risk due to heat stress in Delhi was almost 4 times higher during HW days (5.2% per unit rise in IHI) than on NHW days (1.4% per unit rise in IHI). In Varanasi, the mortality risk is around 2 times during HW days (6.9% per unit rise in IHI) than on NHW days (3.3% per unit rise in IHI).

The gender-specific analysis revealed a risk of 3.7–6.9% (per unit increase in IHI) increase in female mortality and 2.9–6.7% increase in male mortality in Delhi and Varanasi, respectively. In Chennai, the effect of per unit increase in IHI for males was not statistically significant, whereas for females, the mortality risk was 5.3% higher. In terms of differential effects across various age groups, the impact was higher for the population older than 64 years (5.7% in Chennai, 4.2% in Delhi, and 7.5% in Varanasi) than in other age groups. Only in Varanasi the effect on the age group 45–64 years was comparable (7.7%). The effect gradually decreased for the lower age groups in Varanasi but remained comparable in Delhi. In both Chennai and Varanasi, the effect was insignificant for the young adolescent group (<19 years of age).

As part of the sensitivity analysis, we examined the time-lag effects of IHI on excess mortality. We applied a restricted distributed lag model up to 7 days of lag with a polynomial of degree two with eq 1 for all three cities.<sup>43</sup> We found that the effect estimates varied by lag days and remained significant and yielded the highest cumulative effects up to a 3-day lag in Delhi, a

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Figure 5. Estimates of acute effects of IHI on daily all-cause mortality.

4-day lag in Varanasi, and a 6-day lag in Chennai, respectively. After 6 days, the lag effects were found to fade away (Figure 6). The peak in RR (1.036 with 95% CI: 1.029-1.043 or 3.6% with 95% CI: 2.9%-4.3%) was observed for Delhi at 3-days cumulative lag exposure, for Varanasi at 4-days cumulative lag exposure (peak RR = 1.08 with 95% CI: 1.063-1.097 or 8% with 95% CI: 6.3%-9.7%), and for Chennai at 6-days cumulative lag exposure (peak RR = 1.085 with 95% CI: 1.059-1.112 or 8.5% with 95% CI: 5.9%-11.2%). We found a substantially higher risk for the cumulative risk over lag days than a single-day heat stress exposure in both Varanasi and Chennai, where RH is usually higher than that in Delhi.

**3.4. Exposure-Response Relation between IHI and Mortality.** Figure 7 depicts the exposure-response relationship between the IHI and mortality in the three cities. The curves exhibit a significant rise in mortality close to or slightly above the IHI comfort threshold values. The slope of the curves steepens with IHI exposure around 28 °C in Delhi and Varanasi, which is close to the percentile-based "very hot" threshold. In Delhi, which belongs to a semiarid climate, the slope of the curve increases almost linearly past the sweltering threshold until around 33 °C, beyond which its slope slightly reduces.

In Varanasi, the slope of the curve steepens around 32.5 °C IHI, while in Chennai, a significant increase in the slope of the response curve is observed at 29.5 °C IHI, midway between very hot and sweltering classes. Delhi and Varanasi are in northern India where the air temperature frequently goes beyond 40 °C, and the vulnerable condition arises at a little higher range of IHI, while in Chennai, which is a coastal city, the temperature hardly crosses 37 °C, but RH remains very high. The exposure-response curves suggest further refinement of thresholds at the local scale, as the human tolerance to heat stress may change with acclimatization in different geographical conditions.

#### 4. DISCUSSION

In this study, we estimated the mortality risks due to physiological stress during HW and NHW days in three cities in three different climate zones. Currently, in India, the heat management plan is mostly focused on HW days. We showed that physiological stress is high during NHW days too. In four out of five climate zones impacted by heat during peak summer, a large proportion of the NHW days are under sweltering conditions. Heat action plans<sup>7</sup> only consider temperature extremes. HW is determined using only the temperature measurement, and other parameters are not used. Our results showed that humidity is another key parameter for stress, and other factors, such as wind and direct exposure to solar radiation, also affect heat stress conditions. Therefore, ignoring these factors may underestimate or overestimate the actual heat stress condition.  $^{22-24}$  The IHI introduced in this study represents heat stress, considering the parameters responsible for human comfort. It can also be calculated by using common meteorological parameters, which are simulated by climate models. Therefore, the heat stress can be projected for the future using IHI based on climate model outputs.

Based on the current study, it is difficult, though, to fully justify the proposed tolerance thresholds biologically. However, the exposure-response relations suggest that the percentilebased thresholds are quite close to the major breakpoints in the mortality curves. In the future, a physiological model needs to be developed considering factors like metabolic heat exchange and clothing patterns (that interfere with our body's ability to dissipate heat via evaporative cooling by sweating) and linked to IHI to further tune the thresholds targeting various occupational sectors.

Few recent studies reported increasing heat stress vulnerability in Indian cities.<sup>44,45</sup> Our trends of higher female vulnerability to heat stress match with the reported trends in other studies, which reported higher heat stroke events for females (87%) than for males (41%). The same trend was also found in some recent studies<sup>16,35</sup> in small agricultural and industrial work setups. Our results suggest that it is critical to adapt to and mitigate heat exposure through a region-specific heat action plan. The results of our study highlight the



Figure 6. Lag patterns for the IHI effect on excess mortality risk in three cities of India.

heterogeneity in heat stress impacts across diverse climate zones in India. The region-specific heat stress risk thresholds can be useful in formulating zone-specific early warning or mitigative policies by the state weather departments.

With HWs and RH projected to rise in the near future,<sup>46</sup> physiological stress is expected to increase in India across the climate zones, posing a threat to public health and the economy of India. Rapid urban expansion accelerates the warming through the urban heat island effect and contributes to additional stress.<sup>47,48</sup> Even though electrification coverage has significantly improved over the years in India, power demand in peak summer often exceeds the supply, leading to frequent power cuts. This can elevate the health risk further substantially.<sup>46</sup>

Since the current model is based on data from urban areas, the health risks represent the urban population more than the rural population. A systematic approach to compile and collate daily heat mortality data at a finer spatial scale covering both urban and rural areas will further improve the mortality model and its representativeness for India. In India, long-term exposure to heat and its health risk have also unexplored. Coordinated efforts are required to initiate and conduct cohorts to understand this issue.

A few limitations should be noted in our study. Due to the unavailability of daily cause-specific mortality data, all-cause mortality data were used in the study. Heat mortality statistics are available but at the state level.<sup>49</sup> All deaths occurring within the city boundary are registered by the municipal corporations; hence, the nonresidents dying in the city may also impact the death statistics, and this could have led to a marginal inflation in the daily death data in each city. Due to the paucity of health data, we carry out the analysis for the climatically contrasting locations for different time periods. The data for Chennai were only available for the previous decade. However, our analysis is the effect estimate in daily all-cause mortality per unit change in the IHI after adjusting for the confounders, including time. Since the results are expressed in relative terms, the different time periods may not matter. In the future, the analysis can be repeated with data from the same city across different time periods and data from multiple cities at the same time period. We also note that the epidemiological analysis results are derived at a population scale and cannot be directly validated.

The key conclusions of our study are as follows.

 Heat stress on HW days is 1–4 °C higher than on NHW days, but considerable mortality risk remains on NHW days across climate zones.



Figure 7. Exposure-response relationship between IHI and mortality in the three cities. The threshold IHI values for the "very hot" and "sweltering" classes are shown by dashed vertical lines. The shaded region represents 95% CI.

 During sweltering days, each unit rise in IHI leads to an increase in the mortality risk by 5.9, 8.1, and 8% in Delhi, Varanasi, and Chennai, respectively. Heat stress has a lag effect of 3–6 days in the three cities, beyond which the effect fades away.

## ASSOCIATED CONTENT

#### **Supporting Information**

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.3c05218.

Additional figures and data tables giving validation information and descriptive statistics of variables used in the study (PDF)

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R.K.C. and P.J. contributed equally.

## Notes

The authors declare no competing financial interest.

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## REFERENCES

(1) Gasparrini, A.; Guo, Y.; Sera, F.; Vicedo-Cabrera, A. M.; Huber, V.; Tong, S.; de Sousa Zanotti Stagliorio Coelho, M.; Nascimento Saldiva, P. H.; Lavigne, E.; Matus Correa, P.; Valdes Ortega, N.; Kan, H.; Osorio, S.; Kyselý, J.; Urban, A.; Jaakkola, J. J. K.; Ryti, N. R. I.; Pascal, M.; Goodman, P. G.; Zeka, A.; Michelozzi, P.; Scortichini, M.; Hashizume, M.; Honda, Y.; Hurtado-Diaz, M.; Cesar Cruz, J.; Seposo, X.; Kim, H.; Tobias, A.; Iñiguez, C.; Forsberg, B.; Åström, D. O.; Ragettli, M. S.; Guo, Y. L.; Wu, C.; Zanobetti, A.; Schwartz, J.; Bell, M. L.; Dang, T. N.; Van, D.; Heaviside, C.; Vardoulakis, S.; Hajat, S.; Haines, A.; Armstrong, B. Projections of Temperature-Related Excess Mortality under Climate Change Scenarios. *Lancet Planet. Health* **2017**, *1* (9), e360–e367.

(2) Vicedo-Cabrera, A. M.; Scovronick, N.; Sera, F.; Royé, D.; Schneider, R.; Tobias, A.; Astrom, C.; Guo, Y.; Honda, Y.; Hondula, D. M.; Abrutzky, R.; Tong, S.; Coelho, M. S. Z. S.; Saldiva, P. H. N.; Lavigne, E.; Correa, P. M.; Ortega, N. V.; Kan, H.; Osorio, S.; Kyselý, J.; Urban, A.; Orru, H.; Indermitte, E.; Jaakkola, J. J. K.; Ryti, N.; Pascal, M.; Schneider, A.; Katsouyanni, K.; Samoli, E.; Mayvaneh, F.; Entezari, A.; Goodman, P.; Zeka, A.; Michelozzi, P.; de'Donato, F.; Hashizume, M.; Alahmad, B.; Diaz, M. H.; Valencia, C. D. L. C.; Overcenco, A.; Houthuijs, D.; Ameling, C.; Rao, S.; di Ruscio, F.; Carrasco-Escobar, G.; Seposo, X.; Silva, S.; Madureira, J.; Holobaca, I. H.; Fratianni, S.; Acquaotta, F.; Kim, H.; Lee, W.; Iniguez, C.; Forsberg, B.; Ragettli, M. S.; Guo, Y. L. L.; Chen, B. Y.; Li, S.; Armstrong, B.; Aleman, A.; Zanobetti, A.; Schwartz, J.; Dang, T. N.; Dung, Dv.; Gillett, N.; Haines, A.; Mengel, M.; Huber, V.; Gasparrini, A. The Burden of Heat-Related Mortality Attributable to Recent Human-Induced Climate Change. Nat. Clim. Change 2021, 11 (6), 492-500.

(3) Zhao, Q.; Guo, Y.; Ye, T.; Li, S.; Zhao, Q.; Guo, Y.; Ye, T.; Gasparrini, A.; Tong, S.; Overcenco, A.; Urban, A.; Schneider, A.; Entezari, A.; Maria Vicedo-Cabrera, A.; Zanobetti, A.; Analitis, A.; Zeka, A.; Tobias, A.; Nunes, B.; Alahmad, B.; Armstrong, B.; Forsberg, B.; Pan, S.-C.; Íñiguez, C.; Ameling, C.; de la Cruz Valencia, C.; Åström, C.; Houthuijs, D.; van Dung, D.; Royé, D.; Indermitte, E.; Lavigne, E.; Mayvaneh, F.; Acquaotta, F.; di Ruscio, F.; Sera, F.; Carrasco-Escobar, G.; Kan, H.; Orru, H.; Kim, H.; Holobaca, I.-H.; Kyselý, J.; Madureira, J.; Schwartz, J.; K Jaakkola, J. J.; Katsouyanni, K.; Hurtado Diaz, M.; Ragettli, M. S.; Hashizume, M.; Pascal, M.; de Sousa Zanotti Stagliorio Coélho, M.; Valdés Ortega, N.; Ryti, N.; Scovronick, N.; Michelozzi, P.; Matus Correa, P.; Goodman, P.; Hilario Nascimento Saldiva, P.; Abrutzky, R.; Osorio, S.; Rao, S.; Fratianni, S.; Ngoc Dang, T.; Colistro, V.; Huber, V.; Lee, W.; Seposo, X.; Honda, Y.; Leon Guo, Y.; Bell, M. L.; Li, S. Global, Regional, and National Burden of Mortality Associated with Non-Optimal Ambient Temperatures from 2000 to 2019: A Three-Stage Modelling Study. *Lancet Planet. Health* **2021**, *5*, 415–440. (4) Burkatt K. G.; Brauer, M.; Araykin, A. Y.; Godvin, W. W.; Hay, S.

(4) Burkart, K. G.; Brauer, M.; Aravkin, A. Y.; Godwin, W. W.; Hay, S. I.; He, J.; Iannucci, V. C.; Larson, S. L.; Lim, S. S.; Liu, J.; Murray, C. J. L.; Zheng, P.; Zhou, M.; Stanaway, J. D. Estimating the Cause-Specific Relative Risks of Non-Optimal Temperature on Daily Mortality: A Two-Part Modelling Approach Applied to the Global Burden of Disease Study. *Lancet* **2021**, *398* (10301), 685–697.

(5) Parsons, L. A.; Masuda, Y. J.; Kroeger, T.; Shindell, D.; Wolff, N. H.; Spector, J. T. Global Labor Loss Due to Humid Heat Exposure Underestimated for Outdoor Workers. *Environ. Res. Lett.* **2022**, *17* (1), No. 014050.

(6) Hajat, S.; Kosatky, T. Heat-Related Mortality: A Review and Exploration of Heterogeneity. *J. Epidemiol. Community Health* **2010**, 64 (9), 753–760.

(7) Azhar, G. S.; Mavalankar, D.; Nori-Sarma, A.; Rajiva, A.; Dutta, P.; Jaiswal, A.; Sheffield, P.; Knowlton, K.; Hess, J. J. Heat-Related Mortality in India: Excess All-Cause Mortality Associated with the 2010 Ahmedabad Heat Wave. *PLoS One* **2014**, *9* (9), No. e109457.

(8) Green, H.; Bailey, J.; Schwarz, L.; Vanos, J.; Ebi, K.; Benmarhnia, T. Impact of Heat on Mortality and Morbidity in Low and Middle Income Countries: A Review of the Epidemiological Evidence and Considerations for Future Research. *Environ. Res.* **2019**, *171*, 80–91.

(9) Pai, D. S.; Nair, A.; Ramanathan, A. N. Long Term Climatology and Trends of Heat Waves over India during the Recent 50 Years (1961–2010). *MAUSAM* **2013**, *64* (4), 585–604.

(10) Panda, D. K.; AghaKouchak, A.; Ambast, S. K. Increasing Heat Waves and Warm Spells in India, Observed from a Multiaspect Framework. J. Geophys. Res. 2017, 122 (7), 3837–3858.

(11) Rohini, P.; Rajeevan, M.; Srivastava, A. K. On the Variability and Increasing Trends of Heat Waves over India. *Sci. Rep.* **2016**, *6*, No. 26153, DOI: 10.1038/srep26153.

(12) National Crime Records Bureau (NCRB). *Accidental Deaths & Suicides in India*, 2016.

(13) Ray, K.; Giri, R. K.; Ray, S. S.; Dimri, A. P.; Rajeevan, M. An Assessment of Long-Term Changes in Mortalities Due to Extreme Weather Events in India: A Study of 50 Years' Data, 1970–2019. *Weather Clim. Extremes* **2021**, *32*, No. 100315.

(14) Mazdiyasni, O.; Aghakouchak, A.; Davis, S. J.; Madadgar, S.; Mehran, A.; Ragno, E.; Sadegh, M.; Sengupta, A.; Ghosh, S.; Dhanya, C. T.; Niknejad, M. Increasing Probability of Mortality during Indian Heat Waves. *Sci. Adv.* **2017**, *3*, 170006.

(15) Rathi, S. K.; Desai, V. K.; Jariwala, P.; Desai, H.; Naik, A.; Joseph, A. Summer Temperature and Spatial Variability of All-Cause Mortality in Surat City, India. *Indian J. Community Med.* **2017**, *42* (2), 111–115.

(16) Singh, N.; Mhawish, A.; Ghosh, S.; Banerjee, T.; Mall, R. K. Attributing Mortality from Temperature Extremes: A Time Series Analysis in Varanasi, India. *Sci. Total Environ.* **2019**, *665*, 453–464.

(17) Kumar, A.; Singh, D. P. Heat Stroke-Related Deaths in India: An Analysis of Natural Causes of Deaths, Associated with the Regional Heatwave. *J. Therm. Biol.* **2021**, *95*, No. 102792.

(18) Azhar, G.; Saha, S.; Ganguly, P.; Mavalankar, D.; Madrigano, J. Heat Wave Vulnerability Mapping for India. *Int. J. Environ. Res. Public Health* **2017**, *14* (4), 357.

(19) Mishra, V.; Mukherjee, S.; Kumar, R.; Stone, D. A. Heat Wave Exposure in India in Current,  $1.5^{\circ}$ c, and  $2.0^{\circ}$ c Worlds. *Environ. Res. Lett.* **2017**, *12* (12), No. 124012.

(20) Nori-Sarma, A.; Benmarhnia, T.; Rajiva, A.; Azhar, G. S.; Gupta, P.; Pednekar, M. S.; Bell, M. L. Advancing Our Understanding of Heat Wave Criteria and Associated Health Impacts to Improve Heat Wave Alerts in Developing Country Settings. *Int. J. Environ. Res. Public Health* **2019**, *16* (12), 2089.

(21) Grundstein, A.; Cooper, E. Assessment of the Australian Bureau of Meteorology Wet Bulb Globe Temperature Model Using Weather Station Data. *Int. J. Biometeorol.* **2018**, *62* (12), 2205–2213.

(22) Parsons, K. Heat Stress Standard ISO 7243 and Its Global Application. *Ind. Health* **2006**, *44*, 368–379.

(23) Budd, G. M. Wet-Bulb Globe Temperature (WBGT)—Its History and Its Limitations. J. Sci. Med. Sport 2008, 11, 20-32.

(24) Lemke, B.; Kjellstrom, T. Calculating Workplace WBGT from Meteorological Data: A Tool for Climate Change Assessment. *Ind. Health* **2012**, *50*, 267–278.

(25) Coffel, E. D.; Sherbinin, A.; Horton, R. M.; Lane, K.; Kienberger, S.; Wilhelmi, O. The Science of Adaptation to Extreme Heat. In *Resilience: The Science of Adaptation to Climate Change*; Elsevier, 2018; pp 89–103.

(26) Mora, C.; Dousset, B.; Caldwell, I. R.; Powell, F. E.; Geronimo, R. C.; Bielecki, C. R.; Counsell, C. W. W.; Dietrich, B. S.; Johnston, E. T.; Louis, L.; Lucas, M. P.; Mckenzie, M. M.; Shea, A. G.; Tseng, H.; Giambelluca, T. W.; Leon, L. R.; Hawkins, E.; Trauernicht, C. Global Risk of Deadly Heat. *Nat. Clim. Change* **2017**, *7* (7), 501–506.

(27) Vanos, J. K.; Baldwin, J. W.; Jay, O.; Ebi, K. L. Simplicity Lacks Robustness When Projecting Heat-Health Outcomes in a Changing Climate. *Nat. Commun.* **2020**, *11* (1), No. 6079.

(28) Foster, J.; Smallcombe, J. W.; Hodder, S.; Jay, O.; Flouris, A. D.; Havenith, G. Quantifying the Impact of Heat on Human Physical Work Capacity; Part II: The Observed Interaction of Air Velocity with Temperature, Humidity, Sweat Rate, and Clothing Is Not Captured by Most Heat Stress Indices. *Int. J. Biometeorol.* **2022**, *66* (3), 507–520.

(29) Parsons, K. Human Thermal Environments: The Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort, and Performance, 3rd ed.; Routledge, 2013.

(30) Lucas, R. A. I.; Epstein, Y.; Kjellstrom, T. Excessive Occupational Heat Exposure: A Significant Ergonomic Challenge and Health Risk for Current and Future Workers. *Extreme Physiol. Med.* **2014**, *3*, No. 14, DOI: 10.1186/2046-7648-3-14.

(31) Das, B. Thermal Stress, Cardiovascular Stress and Work Productivity among the Female Brick Field Workers of West Bengal, India. J. Hum Ergol. 2018, 47 (1), 1–11.

(32) Balakrishnan, K.; Ramalingam, A.; Dasu, V.; Stephen, J. C.; Sivaperumal, M. R.; Kumarasamy, D.; Mukhopadhyay, K.; Ghosh, S.; Sambandam, S. Case Studies on Heat Stress Related Perceptions in Different Industrial Sectors in Southern India. *Global Health Action* **2010**, 3 (3), 5635.

(33) Sahu, S.; Sett, M.; Kjellstrom, T. Heat Exposure, Cardiovascular Stress and Work Productivity in Rice Harvesters in India: Implications for a Climate Change Future. *Ind. Health* **2013**, *51* (4), 424–431.

(34) Venugopal, V.; Latha, P. K.; Shanmugam, R.; Krishnamoorthy, M.; Omprashanth, R.; Lennqvist, R.; Johnson, P. Epidemiological Evidence from South Indian Working Population—the Heat Exposures and Health Linkage. *J. Exposure Sci. Environ. Epidemiol.* **2021**, *31* (1), 177–186.

(35) Venugopal, V.; Chinnadurai, J. S.; Lucas, R. A. I.; Kjellstrom, T. Occupational Heat Stress Profiles in Selected Workplaces in India. *Int. J. Environ. Res. Public Health* **2016**, *13* (1), 89.

(36) Dash, S. K.; Dey, S.; Salunke, P.; Dalal, M.; Saraswat, V.; Chowdhury, S.; Choudhary, R. K. Comparative Study of Heat Indices in India Based on Observed and Model Simulated Data. *Curr. World Environ.* **2017**, *12* (3), 504–520.

(37) Dey, S.; Choudhary, R. K.; Upadhyay, A.; Dash, S. K. Aerosol-Modulated Heat Stress in the Present and Future Climate of India. *Environ. Res. Lett.* **2021**, *16* (12), No. 124022.

(38) Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Andras, H.; et al. The ERA5 Global Reanalysis. *Q. J. R. Meteorol. Soc.* **2020**, *146* (730), 1999–2049.

(39) Government of India. Census 2011: Office of the Registrar General & Census Commissioner, India. https://censusindia.gov.in/census.website/data/population-finder (accessed April 29, 2023).

(40) Joshi, P.; Ghosh, S.; Dey, S.; Dixit, K.; Choudhary, R. K.; Salve, H. R.; Balakrishnan, K. Impact of Acute Exposure to Ambient PM2.5 on

Non-Trauma All-Cause Mortality in the Megacity Delhi. *Atmos. Environ.* **2021**, 259, No. 118548.

(41) Singh, S.; Mall, R. K.; Singh, N. Changing Spatio-Temporal Trends of Heat Wave and Severe Heat Wave Events over India: An Emerging Health Hazard. *Int. J. Climatol.* **2021**, *41* (S1), E1831–E1845.

(42) Dey, S.; Purohit, B.; Balyan, P.; Dixit, K.; Bali, K.; Kumar, A.; Imam, F.; Chowdhury, S.; Ganguly, D.; Gargava, P.; Shukla, V. K. A Satellite-Based High-Resolution (1-Km) Ambient PM2.5 Database for India over Two Decades (2000–2019): Applications for Air Quality Management. *Remote Sens.* **2020**, *12* (23), 3872.

(43) Schwartz, J. The Distributed Lag between Air Pollution and Daily Deaths. *Epidemiology* **2000**, *11* (3), 320–326.

(44) Kumar, P.; Rai, A.; Upadhyaya, A.; Chakraborty, A. Analysis of Heat Stress and Heat Wave in the Four Metropolitan Cities of India in Recent Period. *Sci. Total Environ.* **2022**, *818*, No. 151788.

(45) Dhorde, A. G.; Desai, M. S.; Dhorde, A. A.; Korade, M. S. Vulnerability of Tropical Indian Cities to Augmenting Heat Stress during Summer and Monsoon Season Months (1969–2015). *Meteorol. Atmos. Phys.* **2022**, *134* (61), No. 61, DOI: 10.1007/s00703-022-00897-3.

(46) Coffel, E. D.; Horton, R. M.; Sherbinin, A. Temperature and Humidity Based Projections of a Rapid Rise in Global Heat Stress Exposure during the 21st Century. *Environ. Res. Lett.* **2017**, *13* (1), No. 014001.

(47) Mondal, S. K.; Wang, Y.; et al. Projected Urban Exposure to Extreme Precipitation over South Asia. *Sci. Total Environ.* **2022**, *822*, No. 153664, DOI: 10.1016/j.scitotenv.2022.153664.

(48) Vinayak, B.; Lee, H. S.; Gedam, S.; Latha, R. Impacts of Future Urbanization on Urban Microclimate and Thermal Comfort over the Mumbai Metropolitan Region, India. *Sustainable Cities Soc.* **2022**, *79*, No. 103703.

(49) Ray, K.; Giri, R. K.; Ray, S. S.; Dimri, A. P.; Rajeevan, M. Ray 2021 An Assessment of Long-Term Changes in Mortalities Due to Extreme Weather Events in India\_ A Study of 50 Years' Data, 1970–2019 \_ Elsevier Enhanced Reader. *Weather Clim. Extremes* 2021, 32, No. 100315, DOI: 10.1016/j.wace.2021.100315.