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Earth's Future

RESEARCH ARTICLE

10.1029/2026EF008395

Special Collection:

Addressing the Escalating Impacts of Extreme Heat, Heat Waves, and Urban Heat Islands on Public Health: Vulnerability, Resilience, and Mitigation Strategies

Key Points:

- We propose a clustering framework to compare thermal metrics and link their differences to meteorological sensitivities
- Perception of nighttime humid heat in low-latitude coastal Asian cities does not capture its risk as indicated by heat stress metrics
- The stress-sensation divergence is explained by a weaker perception of humid heat and a lack of solar radiation as a perception signal

Supporting Information:

Supporting Information may be found in the online version of this article.

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Divergent Heat Assessments Across Thermal Stress and Sensation Metrics

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Abstract A large and growing body of literature has indicated potential inconsistencies in heat assessments due to the use of different heat stress indices (HSI). This divergence hinders the emergence of scientific consensus and impairs the development of public policy on a range of topics, including climate change impacts, public health guidance, and heat adaptation strategies. Beyond discrepancies among physically based HSI themselves, divergence may also arise between physical thermal stress and psychological thermal sensation; such deviation can delay active behavior adaptation measures but has rarely been examined. To explain these metric divergences, we first connect the different assessments of HSI to their varying sensitivities to meteorological drivers and introduce a clustering framework to guide their applications. We then identify spatiotemporal hotspots where sensation-based estimates diverge from HSI-based assessments, highlighting cases where reliance on sensation alone may increase risk. Particularly, nighttime humid heat in low-latitude coastal Asian cities is perceived as less risky than indicated by HSI due to a muted perception of high humidity impact and the absence of solar radiation that would strongly signal heat discomfort. These findings help elucidate inconsistent conclusions in the existing literature stemming from the use of different thermal metrics and localize spatiotemporal hotspots for targeted heat health warning systems.

Plain Language Summary How we evaluate the severity of heat, decide on ways to cool our cities and neighborhoods, and choose personal actions to protect ourselves all depend on how overheating is assessed. However, heat assessments can differ substantially depending on the thermal metric used. To deepen scientific understanding of potential divergence of metric-driven assessments, we propose a clustering framework to identify which metrics tend to perform similarly or differently, and then explain the underlying reasons by linking these differences to their distinct responses to meteorological variability. A notable contrast emerges between thermal stress metrics, which indicate physical environmental heat stress, and thermal sensation metrics, which reflect psychological subjective heat perception. We found that thermal sensation metrics tend to indicate lower heat levels than physically based stress metrics, especially during humid nights in low-latitude coastal Asian cities. This difference occurs because human perception is more sensitive to heat stress driven by high radiation and less sensitive to heat stress driven by high air humidity. These findings help explain divergent evaluations of climate change impacts and adaptation strategies, and suggest when and where heat health warning systems should be strengthened to address heat stress that may be decoupled from subjective estimates.

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1. Introduction

Heat is a pressing environmental and occupational health hazard: epidemiological evidence indicates that heat-waves can precipitate tens of thousands of excess deaths in under-prepared communities within just a few weeks (Robine et al., 2008; Q. Zhao et al., 2021). Reducing individual heat exposure through behavioral adaptation (e.g., shifting work schedules and utilizing cooling centers) serves as a practical and effective stopgap to alleviate overall heat risks (Jay et al., 2021; Johar et al., 2025). Effective implementation of behavioral adaptation relies on two primary triggering pathways: (a) reliable public heat health warning systems (HHWS) (Toloo et al., 2013; WMO, 2015) and/or (b) accurate and timely individual sensation of heat stress levels (Haldi & Robinson, 2010; Li et al., 2024). These two pathways are related to two groups of metrics for characterizing thermal stress and thermal sensation, as depicted in Figure 1 and detailed below.

For HHWS, the selection of the heat indicator is critical. Many existing HHWS are based on temperature, including daily maximum, mean, and/or minimum air temperatures, with risk thresholds often determined from meteorological-epidemiological evidence. However, an increasing number of countries are now using heat stress indices (HSI) to capture the joint impact of multiple meteorological variables (including air temperature, air humidity, wind, and radiative heat exchanges; see left panel in Figure 1) on human health. For example, the United States has used the heat index (HI) to issue heat alerts through the National Weather Service (NWS) since 1984 (Hawkins et al., 2017; NWS, 1984). More recently, in 2021, Japan switched from air temperature to wet bulb globe temperature (WBGT), which has been shown to be a better predictor of daily morbidity than temperature alone (Guo et al., 2024). In addition, the European Centre for Medium-Range Weather Forecasts (ECMWF) has incorporated the universal thermal climate index (UTCI) into ERA5 reanalysis to produce a state-of-the-art bioclimatological data set (ERA5-HEAT) (Di Napoli et al., 2021), which was shown to be well correlated with mortality rate in Europe (Urban et al., 2021), and paves the way for evaluating heat stress in regions without comprehensive meteorological station networks (e.g., Nigeria (Morakinyo et al., 2024)). These studies provide epidemiological evidence that these HSI are good predictors of heat health outcomes.

However, nearly 200 HSI have been proposed over the past century (de Freitas & Grigorieva, 2017; Matzarakis & Nouri, 2022), and there is a lack of consensus on optimal indices or standard protocols to use HSI for heat assessment. The inconsistent adoption of HSI can be problematic since it can lead to diverging, even contrasting, assessments of heat health outcomes and of heat mitigation benefits. Notable examples are that different HSI can produce large disparities in estimated extreme heat severity and associated population exposure (Kong et al., 2025; Schwingshackl et al., 2021), and even yield opposite evaluations of the benefits of evapotranspiration-based heat mitigation strategies (e.g., planting trees (Cheung & Jim, 2018), irrigation (Chakraborty et al., 2025; L. Chen et al., 2025; Yao et al., 2025), and misting (Huang et al., 2025)), likely owing to their different sensitivities to humidity (Sherwood, 2018; Simpson et al., 2023). This would impede accurate assessments of meteorological impacts on heat health, as well as the selection and design of effective heat mitigation strategies. Thus, a comparative analysis is critically needed to elucidate how different HSI align with or diverge from one another, and to clarify the underlying mechanisms in order to better guide their usage.

On the other hand, for regions and populations without access to reliable HHWS (and even sometimes in regions with such systems), individuals largely rely on their own thermal sensation to assess heat stress and decide whether and how to adapt. Thermal sensation is defined as a conscious feeling of the local thermal environment (ASHRAE, 2015). It can be quantified through a thermal sensation vote (TSV), which is graded into numerical categories (e.g., +4 to −4, indicating very hot to very cold), and then encoded in TSV equations based on regression relationships between meteorological conditions and local TSV survey samples. While heat sensation is related to biophysical thermal stress, it is also modulated by other factors such as thermal acclimatization (Brager & de Dear, 1998) (see right panel of Figure 1). When HHWS are not accessible but the actual biophysical risk is present, individuals may fail to take behavioral precautionary measures if their perception underestimates their heat gain from the environment, leading to prolonged exposure and cumulative heat strain (Ban et al., 2019; Haldi & Robinson, 2010; Li et al., 2024). This potential menace underscores the importance of investigating situations in which individuals may not adequately perceive heat despite hazardous conditions, as for example, indicated by an HSI (potentially used in HHWS); these cases are hereafter referred to as “*unperceived stress scenarios*.” Unperceived stress scenarios have never been examined at a global scale, possibly because most TSV equations are developed for specific local climate conditions, while globally applicable TSV models remain limited.

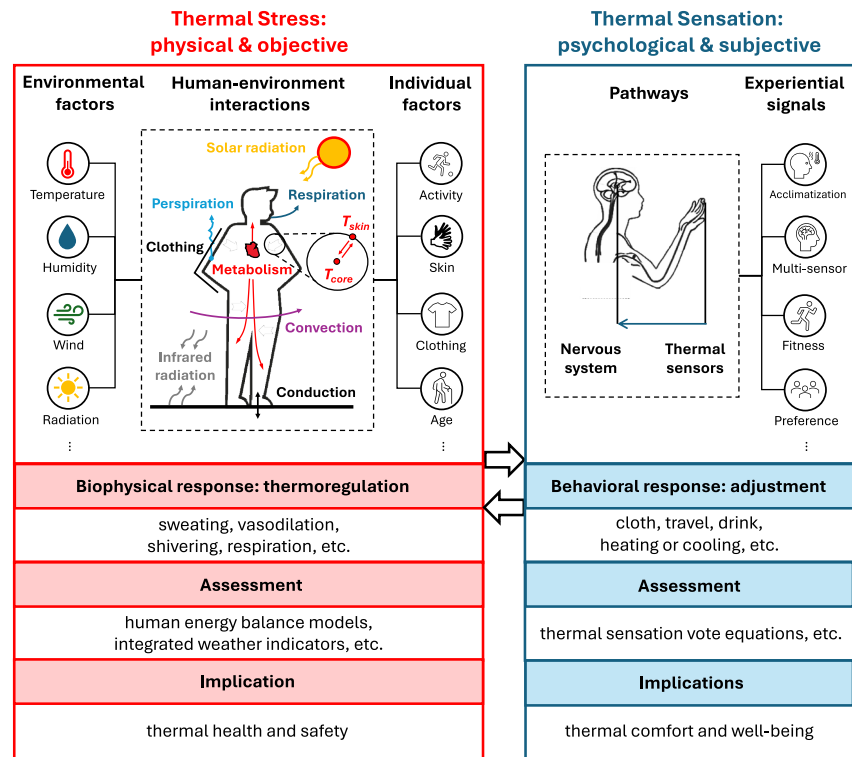


Figure 1. Schematics of thermal stress and thermal sensation.

Building on the research background above, we outline two open challenges in heat assessment: (a) which HSI exhibit divergent or similar behavior, and what mechanisms drive these distinctions; and (b) when, where, and why HSI-based assessment and sensation-based estimation tend to diverge. To answer these two questions, we first conduct correlation and clustering analysis to identify HSI cohorts that tend to perform similarly or divergently; then, we explain the clustering results by quantifying the sensitivity of each HSI to key meteorological variables by Markov-Chain Monte-Carlo (MCMC) subset simulations. We follow by investigating the spatio-temporal hotspots and meteorological conditions under which unperceived stress scenarios tend to occur, using local TSV models as well as a climate-adaptive TSV metamodel developed here from a meta-analysis of 33 existing TSV equations worldwide.

2. Materials and Methods

2.1. Meteorological Data Sets

We selected the 100 most populous cities according to 2015 population data from the World Urbanization Prospects report (United Nations, 2019), with broad representation of climate types and geographic regions. These cities include 84 cities from the Northern Hemisphere, including 23, 11, and 9 cities in China, the USA, and India, respectively; and 16 cities from the Southern Hemisphere. To gather meteorological data sets for these cities, we collected hourly 2-m air temperature (T), 2-m air relative humidity (H), and 10-m wind speed (W) from the ERA5 reanalysis (Hersbach et al., 2020), and collected surface-level mean radiant temperature (R) from the ERA5-HEAT data set (Di Napoli et al., 2021).

The collected data span three summer months (JJA for the Northern Hemisphere; DJF for the Southern Hemisphere) over 10 years from 2010 to 2019. This resulted in a large meteorological data set for the 100 cities ($24 \text{ hr} \times 90 \text{ days} \times 10 \text{ years} \times 100 \text{ cities} = 2,160,000$ data points, approximately). We force the eight thermal models (detailed in Sections 2.2 and 2.3) with these meteorological observations to identify inter-model correlation and discrepancies in real-world applications. We also used statistical measures (maximum, minimum, mean, and standard deviation; as shown in Table 1) of each meteorological variable to drive MCMC sampling. Note that these meteorological variables are randomly combined in the MCMC simulations to represent numerous

Table 1

Meteorological Statistics for MCMC Subset Simulation, Based on Aggregated Meteorological Observations for 100 Cities Worldwide During Summer Months Over 10 Years

	Maximum	Minimum	Mean	Standard deviation
Air temperature (T , °C)	37.6	15.8	25.6	3.4
Relative humidity (H , %)	98	26	72	13
Wind speed (W , m/s)	10.64	0.03	3.03	1.39
Mean radiant temperature (MRT, °C)	60.2	7.4	32.1	14.3

Note. The maximum and minimum are the extrema of the mean summer temperatures of the 100 cities, and the standard deviation is for the mean temperature of these cities.

possible meteorological conditions, including those with low probabilities of occurrence but which could lead to extreme heat events; and the vast majority of probability density functions (PDFs) realizations fall within the bounds of historical climates (Hersbach et al., 2020), implying they are plausible to occur under real-world climatic conditions.

Note that we use relative humidity instead of absolute atmospheric moisture contents because: (a) relative humidity is dominantly used in existing TSV equations and developing a TSV metamodel based on specific/absolute humidity is thus not feasible; and (b) in MCMC simulations, meteorological variables are independently sampled so the relationship of relative humidity and air temperature is decoupled for sensitivity tests, that is, switching to specific humidity, absolute humidity, or vapor pressure would not alter the sensitivity results.

For TSV application, the essential assumption is that of quasi-steady-state thermal conditions for the human body, which are usually achieved within 10–20 min of exposure to a fixed meteorological state (Givoni et al., 2003; Golasi et al., 2018; Hadianpour et al., 2018; Vellei et al., 2021; L. Zhao et al., 2016). In our implementation, the use of hourly ERA5 data should thus be interpreted as representing hourly averaged environmental conditions. Given that perceptual adjustments to outdoor thermal environments typically occur on timescales (10–20 min) less than an hour, the hourly resolution provides a reasonable approximation of quasi-steady-state exposure conditions. This approach also aligns with the common timescales of thermal stress evaluation, thus enabling comparison of thermal stress and sensation results.

2.2. Heat Stress Indices

In this study, we selected seven HSI: wet-bulb temperature (T_{wb}), wet-bulb globe temperature (WBGT), standard effective temperature (SET), universal thermal climate index (UTCI), modified physiologically equivalent temperature ($mPET$), heat index (HI), and apparent temperature (AT). The selection of these seven HSI is based on their wide application (covering the majority of previous thermal stress/comfort studies (Potchter et al., 2018)), diverse levels of sophistication in representing human thermo-physiology, and preferences of different research communities and HHWS.

In this work, we coded the seven thermal metrics in MATLAB™ based on widely used open-access repositories (Brimicombe et al., 2022; Tartarini & Schiavon, 2020) and other important references (Liljegren et al., 2008; Lu & Roms, 2022; R. G. Steadman, 1984; Walther & Goestchel, 2018). Due to data availability and to ensure comparability, we made the following assumptions and processing. (a) For two models ($mPET$ and SET) that need specific human parameters, we use an average human setting with a body height of 1.7 m and a body weight of 60 kg, and a typical clothing condition of 0.3 clo in summer (Lee et al., 2013). We prescribe the metabolic rate of a 30-year-old female. (b) Most models use 10-m wind speed as input, the same height as in our wind speed data set (ERA5); for WBGT, which uses 2-m wind speed, we transferred the 10-m wind speed (W_{10m}) to 2-m wind speed (W_{2m}) via the following simplified neutral logarithmic wind profile: $W_{2m} = W_{10m} \log(2/0.01) / \log(10/0.01)$ (Oke, 1987), where the 0.01 m is the momentum roughness length of the surface (assumed relatively smooth, and thus similar to the surfaces recommended for reference weather stations by the World Meteorological Organization (Oke, 2006)). (c) We use MRT as the radiation input, as in the original settings in most models (WBGT, SET, UTCI, and $mPET$); for AT, we assume fixed skin temperatures (36°C), considered as an acceptable approximation for hot conditions, to calculate human radiation budgets. (d) UTCI has a lower limit of

0.5 m/s in wind speed, but we also calculate UTCI values when wind speed is below 0.5 m/s to allow thorough comparison to other metrics. We find $U < 0.5$ m/s only constitutes a small portion (around 2%) for all scenarios, and this range of wind speed (or generally low wind speed) is not relevant to the stress-sensation divergence as we show later.

2.3. Meta-Analysis of Thermal Sensation Votes

In this study, we conducted a meta-analysis of empirical TSV equations and developed a climate-adaptive TSV metamodel for global application. To assess how people perceive and evaluate the thermal environment, a common approach is to conduct questionnaires to record people's perceptions as TSVs. The TSV metric quantifies people's subjective perceptions on a Likert scale (Likert, 1932): for example, with a 9-point scale TSV, people report their perception of the thermal environment with a numerical vote from -4 to $+4$ during field surveys. The sign means that people feel hot (+), neutral (0), or cold (−), and the magnitude reports the level of discomfort: the smaller the absolute value, the more neutral/comfortable a person feels. For example, $+4$ means very hot and $+1$ means slightly warm. Ideally, field surveys would be combined with in situ meteorological measurements of temperature, humidity, wind speed, and radiation, though some surveys omit the last two variables. Note that these TSV equations are designed to capture sensation-meteorology relationships in outdoor spaces, while they may be useful indoors, air-conditioning would decouple them from the ambient meteorology; this is out of the scope of the present analysis.

By performing linear regression between the collected TSV data and simultaneous meteorological measurements, TSV equations have been developed in many regions. Their general formulation follows

$$\text{TSV} = C_T T + C_H H + C_W W + C_R R + C \quad (1)$$

where C_i is the coefficient of variable i describing the impact of that meteorological variable on human thermal sensation, and i can refer to T (air temperature, °C), H (air humidity; e.g., relative humidity in this study, %), W (wind speed, m/s), or R (radiation; e.g., mean radiant temperature, MRT, in this study, °C). All C_i 's, as well as C , are empirical fitting coefficients. During a TSV survey, T , H , W , and R refer to the simultaneously monitored meteorological data to which the individual is exposed for a sufficient duration so that their sensation equilibrates with these conditions; therefore, during equation application, T , H , W , and R should be interpreted as the quasi-steady-state meteorological conditions experienced by the individual (i.e., the time-scale over which the meteorology varies $\gg$ thermal equilibration time scale of the human).

These TSV equations are powerful tools to translate measurable meteorological variables into subjective human sensation. However, almost all TSV equations were developed locally, that is, based solely on TSV and meteorological data sets collected from specific cities. This limitation results in a significant discrepancy in the magnitudes, and even signs, that are adopted in different equations. Such a large discrepancy implies that constant coefficients from linear regression may not be suitable for capturing the impacts of meteorological changes on thermal sensation in different climates. The reasons are related to both thermal transfer and biophysical acclimatization. On the one hand, human-environment heat exchange is non-linearly driven by contrasts between the human surface (skin or clothing) and the surrounding environment, particularly through convection, radiation, and evaporation. People adapt their clothing and behavior to fit their ambient climate. In addition to such external adaptations, human perception is also affected by other experiential factors, including environmental experiences, memory, expectation, and culture, which shape a particular thermal comfort niche for people from different regions. e.g., previous studies have shown that neutral temperatures (i.e., the temperature where people feel neither warm nor cool) can vary dramatically from 13°C in Fribourg, Switzerland (Nikolopoulou & Lykoudis, 2006), to 28.6°C in Phoenix, USA (Middel et al., 2016). This is clear evidence that coefficients in TSV equations strongly depend on regions and their background climates, which prompted us to examine the relationship between coefficients and meteorological variables more closely.

To this end, we conducted a meta-analysis consisting of six phases: (a) review previous studies that contain TSV equations and report ranges/averages of meteorological variables used to derive these equations; (b) collect and standardize TSV coefficients and average values of meteorological variables; (c) identify potential statistical relationships between the coefficient and the averaged meteorology by calculating Spearman rank coefficients

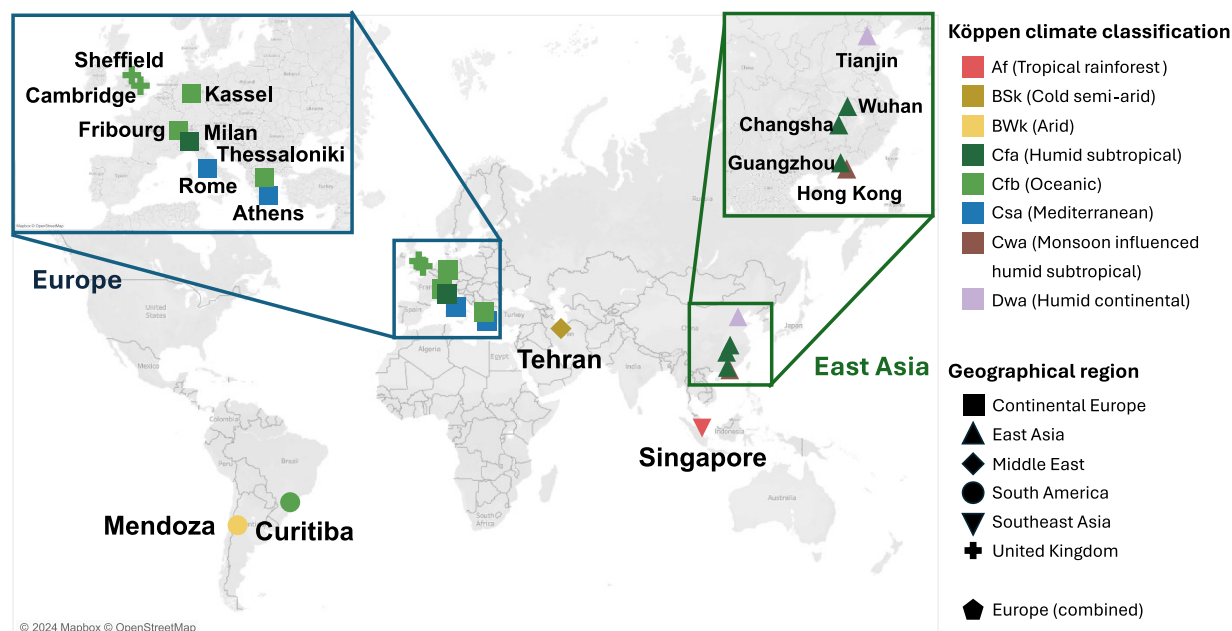


Figure 2. Geographical locations of the 17 cities where 33 collected TSV equations are developed, from 11 countries across 8 Köppen climate types and 6 geographical regions.

and their statistical significance levels; (d) explore and fit the relationships between coefficients and meteorological parameters that show relatively strong dependence; (e) use the fitted relationships to develop a climate-adaptive TSV metamodel for global application; and (f) evaluate the developed TSV metamodel against two comprehensive thermal comfort databases. Here, we elaborate on the literature review (phase 1) and data collection (phase 2). More results about phases 3–6 are presented in Section 3.1.

In phase 1, we reviewed 121 peer-reviewed journal articles engaging in outdoor thermal questionnaires and meteorological measurements. These articles were collected by searching “(thermal (comfort OR perception)) AND (questionnaire OR survey)” in the Web of Science database, and considered all articles listed in the review section of two important articles (Feng et al., 2021; Potchter et al., 2018). Most of these articles analyzed TSV data sets and used them to calibrate the local thermal scales of thermal stress models without developing a TSV equation. Only 12 articles that developed a TSV equation and reported ranges/averages of the meteorological parameters during the experiment were selected. From these 12 articles, we compiled 33 TSV equations for 17 cities across 11 countries encompassing 8 Köppen climate types and 6 geographical regions. The data set represents diverse climates in Europe, East Asia, South America, Southeast Asia, and the Middle East, laying a foundation for developing a climate-adaptive TSV metamodel. Figure 2 shows the geographical distributions and Köppen climate types of the 17 cities, and Table 2 shows the collected 33 TSV equations, studied cities, countries, TSV scales, minimum/average/maximum values of meteorological variables, and references. All 33 collected TSV equations, and their meteorological background, are then used to produce the global TSV metamodel, which will be applied to examine “unperceived stress” in Figures 6a2, 6b2, and 6c2. Additionally, 17 of these equations (denoted with ** in Table 2) are further used as original local TSV equations (Figures 6a1, 6b1, and 6c1) to confirm that our conclusions regarding summertime “unperceived stress” phenomenon are not altered by the choice of global versus local TSV models. The number (17) of used local TSV equations is smaller than the total collected number (33) because one city might have multiple TSV equations developed for different seasons, but here we only use the TSV equation tailored for summertime application.

In phase 2, we extracted and processed coefficients from the 33 TSV equations and average values of meteorological variables. Collected data are standardized in two ways: (a) TSV may be reported in different scales, for example, TSV recorded as +4 to −4 or as +3 to −3 cannot be compared directly. Thus, we standardized different scales to a 9-point scale (with a maximum TSV of 4, i.e., ranging from +4 to −4). (b) Several variables are used to describe humidity (relative or absolute humidity) and radiation (MRT, solar radiation intensity, and globe

Table 2
The 33 TSV Equations, Including the Study's City, Country, Maximum TSV, Minimum/Average/Maximum Values of Meteorological Variables, and References

City	Country	Max TSV	TSV equation ^a	Minimum, average, maximum				Ref.
				T (°C)	RH (%)	V (m/s)	MRT (°C)	
Athens	Greece	2	TSV = 0.034 T + 0.0001SR - 0.086 V - 0.001RH - 0.412 ^b	16,22,30	47,53,62	0.7,0.9,1.1	/	Nikolopoulou (2004)
Thessaloniki		2	TSV = 0.036 T + 0.0013SR - 0.038 V + 0.011RH - 2.197 ^b	10,18,27	41,54,63	0.2,0.2,0.2	/	
Fribourg	Switzerland	2	TSV = 0.068 T + 0.0006SR - 0.107 V - 0.002RH - 0.69 ^b	7,14,23	43,53,62	1.0,1.1,1.2	/	
Milan	Italy	2	TSV = 0.049 T - 0.0002SR + 0.006 V + 0.002RH - 0.920 ^b	11,19,26	56,60,63	0.5,0.5,0.6	/	
Cambridge	UK	2	TSV = 0.113 T + 0.0001SR - 0.05 V - 0.003RH - 1.74 ^b	9,16,23	56,61,74	0.5,0.8,1.0	/	
Sheffield		2	TSV = 0.07 T + 0.0012SR - 0.057 V - 0.003RH - 0.855 ^b	10,15,21	49,60,69	0.5,0.7,1.0	/	
Kassel	Germany	2	TSV = 0.043 T + 0.0005SR - 0.077 V + 0.001RH - 0.876 ^b	10,15,21	58,65,76	0.5,0.7,1.0	/	
Combined model for above 7 European cities		2	TSV = 0.049 T + 0.001SR - 0.051 V + 0.014RH - 2.079	7,17,30	41,58,76	0.2,0.7,1.2	/	
Curitiba	Brazil	4	TSV = 0.13 T - 0.27 V + 0.0007SR - 2.31 ^b	6,20,31	23,58,93	0.0,1.7,3.3	10,41,72	Krüger and Rossi (2011)
Hong Kong	China	3	TSV = 0.1895 T + 0.0028SR - 0.7754 V + 0.1953RH - 2.3 (Summer) ^b	24,28,31	80,81,81	/	/	Ng and Cheng (2012)
		3	TSV = 0.1185 T + 0.0025SR - 0.6019 V + 0.1155RH - 4.77 (Summer and Winter)	13,22,31	60,70,81	/	/	
Changsha	China	3	TSV = 0.313 T + 0.030MRT - 0.304 V + 0.026RH - 11.622 ^b	26,32,38	40,65,90	0.1,0.9,3.2	26,34,65	Yang et al. (2013)
Singapore	Singapore	3	TSV = 0.398 T + 0.038MRT - 0.329 V + 0.023RH - 14.061 ^b	26,31,36	48,70,91	0.1,1.0,4.5	26,35,64	
Wuhan	China	1	TSV = 0.0643 T + 0.00076SR - 0.161 V - 0.00376RH - 1.382 ^b	17,25,36	38,62,92	0.0,0.8,2.8	/	Lai et al. (2014)
Mendoza	Argentina	2	TSV = 0.0621 T - 0.3257 V + 0.0079RH - 0.9796 ^b	-1,18,35	15,36,69	0.0,2.2,6.7	/	Ruiz and Correa (2015)
Guangzhou	China	3	TSV = 0.245 T + 0.059MRT - 0.457 V + 0.013RH - 8.527	25,30,35	38,63,90	0.0,0.7,3.5	26,34,66	L. Zhao et al. (2016)
Rome	Italy	3	TSV = 0.058 T + 0.083MRT - 0.272 V + 0.005RH + 0.264CLO - 4.068 ^b	3,20,36	34,63,92	0.0,1.3,2.5	8,28,48	Salata et al. (2016)
Changsha	China	4	TSV = 0.146 T - 0.007AH - 0.308 V + 0.097 Tg - 2.819 (All year)	2,22,40	16,61,95	0.0,0.9,4.3	/	Liu et al. (2016)
		4	TSV = 0.172 T - 0.041AH - 0.191 V + 0.042 Tg - 2.779 (Spring)	10,21,35	16,58,95	0.0,0.7,2.7	/	
		4	TSV = 0.236 T + 0.015AH - 0.325 V + 0.091 Tg - 5.886 (Summer)	19,30,40	28,60,90	0.0,0.9,3.7	/	
		4	TSV = 0.112 T - 0.011AH - 0.373 V + 0.110 Tg - 2.297 (Autumn)	6,18,34	27,62,91	0.0,0.9,3.5	/	
		4	TSV = 0.121 T + 0.102AH - 0.464 V + 0.111 Tg - 2.882 (Winter)	2,8,17	30,66,86	0.0,0.9,3.5	/	
Tianjin	China	1	TSV = 0.077 T + 0.708Pw + 0.00159ACT + 0.949CLO - 0.0666AGE - 2.646 ^b	-5,20,35	/	/	/	Lai et al. (2018)
Tehran	Iran	3	TSV = 0.101 T + 0.028MRT - 0.233 V - 0.002RH - 2.681 (All year)	3,23,38	9,25,66	0.1,1.1,4.1	0,25,49	Hadiampour et al. (2018)
		3	TSV = 0.120 T + 0.014MRT - 0.218 V - 2.799 (Spring)	11,26,38	10,21,44	0.4,1.6,4.1	5,29,49	
		3	TSV = 0.212 T + 0.058MRT - 0.285 V + 0.05 RH - 8.173 (Summer) ^b	27,33,38	10,16,27	0.4,1.0,3.2	28,36,47	
		3	TSV = 0.149 T + 0.004MRT - 0.367 V + 0.020RH - 3.821 (Fall)	15,24,35	16,25,37	0.1,0.8,2.2	9,25,52	
		3	TSV = 0.173 T - 0.009MRT - 0.457 V - 0.003RH - 2.703 (Winter)	3,10,19	15,38,66	0.1,1.0,3.8	0,9,21	
Guangzhou	China	4	TSV = 0.197 T - 0.373 V + 0.014MRT + 0.002RH + 0.161CLO + 0.141 M-4.741 (all year)	10,25,37	36,64,94	0.0,0.5,4.7	10,31,75	Feng et al. (2021)
		4	TSV = 0.223 T - 0.376 V + 0.033MRT - 5.406 (Spring)	21,28,34	46,69,89	0.0,0.4,3.1	13,34,57	
		4	TSV = 0.175 T - 0.825 V + 0.021MRT + 0.153 M-4.036 (Summer) ^b	27,32,37	50,72,94	0.0,0.3,2.5	21,37,75	
		4	TSV = 0.309 T + 0.007RH - 9.151 (Fall)	19,24,29	47,59,78	0.0,0.7,3.4	19,32,64	
		4	TSV = 0.209 T - 0.171 V + 0.248 M-4.666 (Winter)	10,16,22	36,55,87	0.0,0.6,4.7	10,20,46	

Note. The symbols for meteorological variables are not all similar to the T, H, W, and R used in this study; the meaning of each symbol has thus been explained in the footnote ^a. ^aUsed parameters in TSV equations: T: air temperature (°C); RH: air relative humidity (%); V: wind speed (m/s); MRT: mean radiant temperature (°C); AH: absolute humidity (g/m³); T_g: globe temperature (°C); SR: short-wave radiation (W/m²); P_w: water vapor pressure (kPa); ACT: activity level (W); CLO: clothing (clo); AGE: age, -1 for less than 30 years old, 0 for 30–60 years old, and +1 for more than 60 years old; M: metabolic rate (Met). ^bThe 17 TSV equations used for unperceived stress analysis as in Figure 6a1.

temperature). Here, we only collect relative humidity (%) and MRT (°C), which are the variables most studies have used, ignoring other variables.

2.4. Markov Chain Monte-Carlo Subset Simulation

To quantify the sensitivity of a thermal stress model, the most straightforward approach is to evaluate the partial change by varying individual meteorological parameters one at a time, while the other parameters are kept unchanged (Charalampopoulos, 2019; Provençal et al., 2016). However, this approach is inefficient for capturing the occurrence of extreme events with low probability of occurrence in model output (the distribution tails), especially with a growing parameter space that would require rapidly increasing computational resources. It is also challenging to then compare different models (with varying magnitudes) and various meteorological variables (with differing meanings and units). Another significant limitation of this approach is that the sensitivities might depend on the base values of the parameters for nonlinear problems, which then would require an even more computationally demanding full factorial analysis.

To overcome these limitations, we employ stochastic subset simulation based on the MCMC algorithm, which is efficient in simulating extreme events with short-tail probabilities, and is robust at high dimensionality (Au & Beck, 2001). The theoretical basis is to express the extreme probability as a product of larger conditional probabilities by introducing intermediate probability events, thereby converting an extreme event simulation problem into a sequence of more frequent ones. The exceedance probability $P(Y > y)$ is defined as the probability P of a critical response Y exceeding a threshold level y . A smaller exceedance probability P indicates a more extreme event.

The procedures of MCMC subset simulation are as follows. (a) At the initial phase (level 0), input parameters follow a prescribed PDF (e.g., normal distributions for meteorological parameters) in the same way as in a direct Monte Carlo method. (b) At the end of the initial stage, conditional samples at the next level (level 1) are defined using a given intermediate conditional probability p_0 . e.g., $p_0 = 0.1$ means that 10% of the level 0 samples that result in the top 10% of the monitored output (e.g., thermal stress) will be selected as conditional samples at level 1. (c) Subsequent conditional samplings are simulated by MCMC with the intermediate exceedance probability target, that is, $P(Y > y_i) = p_0^i$ ($i = 1, 2, 3, \dots$ denoting conditional levels), until simulations reach the final target with $p_f = p_0^N$, where p_f is the target probability of a rare event and N the total number of conditional levels. Using this method, a rare event, e.g., with target exceedance probability of $p_f = 0.1^3$ (i.e., the probability of occurrence is less than 0.1%), can be effectively broken down into four different sampling levels (one unconditional Monte Carlo simulation and three subsequent conditional MCMC); each sampling a moderate conditional probability of $p_0 = 0.1$.

In this study, we employ MCMC simulation to evaluate the sensitivity of various thermal metrics to meteorological inputs. The meteorological variables are subject to chaotic atmospheric dynamics with high variabilities, making MCMC simulations suitable for probing extreme heat scenarios that can result from the joint variability of multiple stochastic meteorological inputs. To carry out the subset simulation, we define the critical level ($p_0 = 0.1$), the number of levels ($N = 3$), and an extremely large number of simulations ($n = 25,000$) at each level to minimize the statistical uncertainty (L. Chen et al., 2021). We tested seven thermal stress metrics (monitored output: thermal stress) and the developed climate-adaptive TSV metamodel (monitored output: TSV, see the following section for details). Normal distributions were constructed from aggregated meteorological statistics of 100 cities worldwide (Table 1) to initialize the direct Monte Carlo phase (i.e., level 0). Maxima, minima, means, and standard deviations were first calculated for each city, and then aggregated across all cities to derive the parameters for MCMC simulations, thereby avoiding unrealistically extreme weather conditions.

The deviation between conditional and unconditional samples at different levels is computed to determine the sensitivity of monitored outputs to individual inputs. A large deviation of the conditional sample distribution from the predefined distribution suggests a high sensitivity of the monitored output to the studied input variable. To evaluate the deviation level, we adopted the Standard Score (SS, Equation 2) as the sensitivity measure:

$$SS = \frac{E[X|Y > y_N] - E[X]}{\sigma[X]} \quad (2)$$

where $E[X|Y > y_N]$ is the expected value of parameter X at the most extreme conditional level N , $E[X]$ the prescribed mean of the unconditional distribution of the parameter, y_N the critical response at conditional level N with lowest exceedance probability, and $\sigma[X]$ the prescribed standard deviation of the parameter. The magnitude of the SS indicates the sensitivity (deviation of conditional means), and its sign indicates the sign of the correlation between the monitored output and the uncertain input parameter (+: positive; -: negative). It should be noted that sensitivity here is purely a model property and does not equal the impact (= sensitivity $\times$ change) of a meteorological variable (this is thus not a variance attribution analysis). For example, to evaluate the cooling benefits of urban heat mitigation strategies, both the sensitivity of thermal stress metrics to meteorological changes (from a physiological perspective) and the maximum possible microclimatic modifications (from an environmental perspective) should be considered together. We employed MCMC subset simulations to test the sensitivity of the developed climate-adaptive thermal sensation model and seven thermal stress metrics to meteorological variables. In our analysis later in the paper, we will use SS at the first exceedance levels, that is, $N = 1$, with an exceedance probability of 10% representing common summertime conditions, to analyze model sensitivity. We also examined the SS of thermal metrics at higher exceedance levels, with exceedance probabilities of 1% (Figure S1b in Supporting Information S1) and 0.1% (Figure S1c in Supporting Information S1), which revealed that the meteorological sensitivities of the analyzed thermal metrics diverge even more under extreme heat conditions.

3. Results and Discussion

3.1. Development and Evaluation of a Climate-Adaptive TSV Metamodel

To investigate how background climate regulates the meteorology-sensation relationship, we calculate Spearman rank coefficients (r_s) and corresponding p -values for 16 pairs of 4 meteorological variables (T , H , W , R) and 4 coefficients (C_T , C_H , C_W , C_R), as shown in Figure 3. We observed that T and R dominate in regulating the impacts of all meteorological variables: T and R generally have stronger and more significant correlations with all coefficients (see large bubbles and more stars in the first and fourth lines of Figure 3a). For example, Figure 3b shows how the humidity coefficient (C_H) is regulated by changes in T and R . We found that human perception to H is only acute in high-temperature high-radiation regions: C_H tends to increase with T and R , and a non-negligible C_H often appears with a T over 27.5°C and an R over 32.5°C, which corresponds to typical summer scenarios for four cities (Tehran, Singapore, Guangzhou, and Changsha). Note that Figure 3b simply illustrates the collective control of T and R over H ; it is not directly used for regression.

To further investigate how temperature and radiation shape the impacts of each meteorological variable, we plotted the strongest and most statistically significant relationship for each coefficient (i.e., the largest bubble for each column in Figure 3a) in Figure 3c. Temperature is more dominant in regulating its impact (C_T , left top panel) and that of wind (C_W , left bottom panel), while radiation is more dominant in regulating its impact (C_R , right bottom panel) and that of humidity (C_H , right top panel). Note that for the humidity impact (C_H), the coefficient is jointly controlled by two interdependent factors (T and R , as shown in Figure 3b); thus, we select the more influential factor (radiation, R) to plot and fit the relationship. For each relationship, we fit a quadratic function as shown in subfigures, considering observed patterns, physical mechanisms, and satisfactory fitting performance. We also consider physical constraints, especially in regions with scarce data; for example, we use constant values (the intercepts of fitting functions at $R = 20^\circ\text{C}$) when R is lower than 20°C to avoid unrealistic scenarios such as a negative C_R .

The minimum of the temperature coefficient curve ($C_T = f(T)$) and the maximum of the wind coefficient curve ($C_W = f(T)$) both occur at an intermediate T between 15 and 17°C. The two non-monotonic relationships can be attributed to competing wind effects, with convective cooling dominant in cold conditions and evaporative cooling dominant (over convective heating) in hot conditions. The temperature impact (C_T) stays moderate (below 0.3°C^{-1}) when T is below 25°C, but soars in hot regions, which can be explained by the limited effectiveness, or even possible failure, of human thermoregulation under high temperatures (Cramer & Jay, 2016). A similar trend is observed in the radiation coefficient curve ($C_R = f(R)$), albeit less pronounced due to the limited available data.

Based on the fitted relationships between coefficients and variables in the meta-analysis, we developed the following climate-adaptive TSV metamodel, which can be used more broadly across the globe (Equation 3):

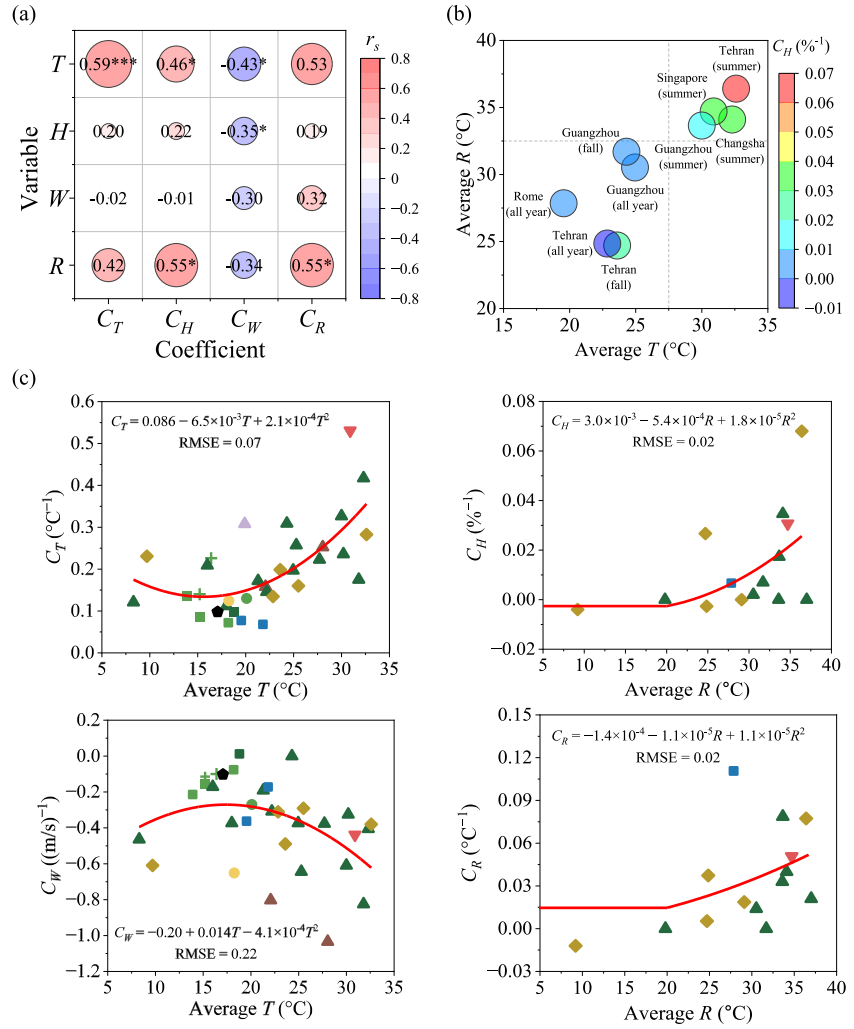


Figure 3. (a) Spearman rank coefficient (r_s) for all pairs of variables and coefficients, with statistical significance levels denoted by the numbers of stars (*: p -value < 0.05; **: p -value < 0.01; ***: p -value < 0.001). (b) Humidity coefficient (C_H) under different air temperatures (T) and mean radiant temperatures (R), which are average values during the TSV survey periods; and (c) the selected pairs with strong correlation and their fittings (same legends as in Figure 2 for region and climate).

$$\begin{aligned}
 \text{TSV} &= C_T T + C_H H + C_W W + C_R R + C \\
 \left\{ \begin{aligned}
 C_T &= 0.086 - 6.5 \times 10^{-3}T + 2.1 \times 10^{-4}T^2 \\
 C_H &= 3.0 \times 10^{-3} - 5.4 \times 10^{-4}R + 1.8 \times 10^{-5}R^2 \quad (R > 20); \quad C_H = -8.1 \times 10^{-4} \quad (R \leq 20) \\
 C_W &= -0.20 + 0.014T - 4.1 \times 10^{-4}T^2 \\
 C_R &= -1.4 \times 10^{-4} - 1.1 \times 10^{-5}R + 1.1 \times 10^{-5}R^2 \quad (R > 20); \quad C_R = 4.1 \times 10^{-3} \quad (R \leq 20) \\
 C &= -1.75
 \end{aligned} \right. \quad (3)
 \end{aligned}$$

where C_T , C_H , C_W , C_R are fitted as shown in Figure 3c, and all coefficients, including C , are calibrated to TSV data calculated from the collected local TSV equations.

We evaluated the performance of the developed climate-adaptive TSV metamodel against two thermal comfort questionnaire databases: (a) the Rediscovering the Urban Realm and Open Spaces (RUROS) project

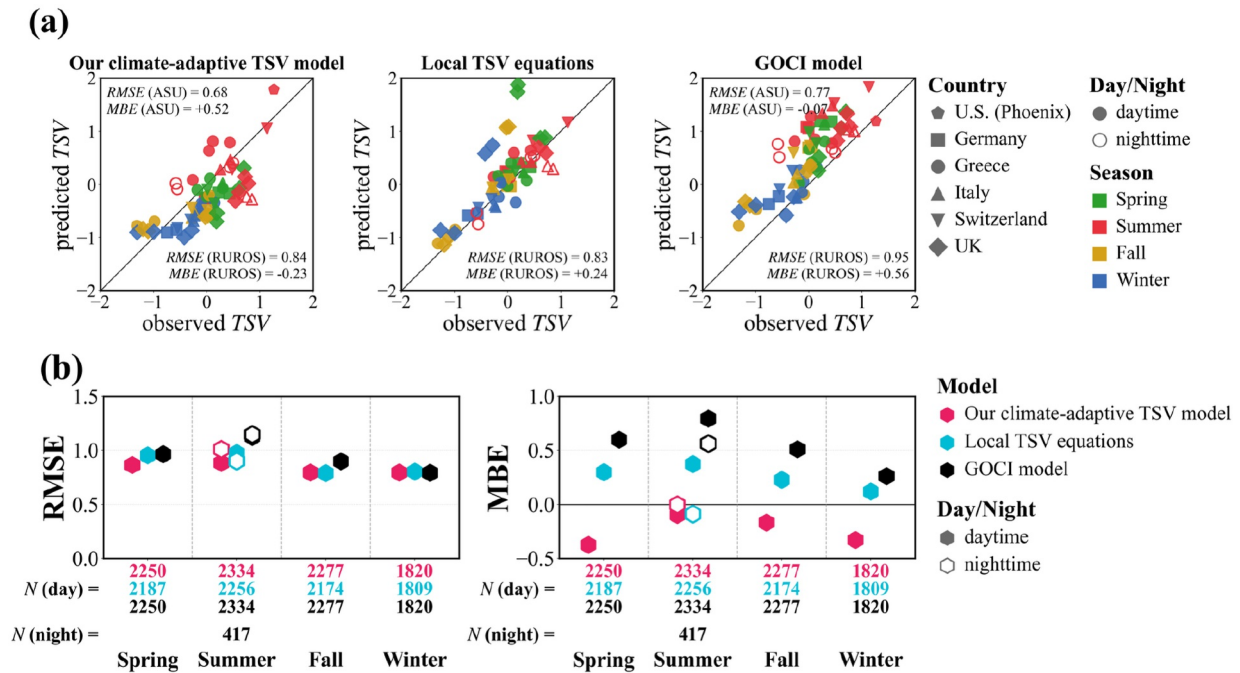


Figure 4. (a) Predicted TSV by our climate-adaptive TSV model, local TSV equations (the first seven equations in Table 2) and the GOCI model against observation from RUROS and ASU data sets. (b) Breakdown of RMSE and MBE by season and by daytime/nighttime for each model, where each dot represents the metric value for a given group and the numbers below the x-axis indicate the corresponding sample size.

(Nikolopoulou & Lykoudis, 2004) and (b) the Arizona State University campaign (Middel et al., 2016). The RUROS database is the most comprehensive TSV database with a large sample size (9271 data points) and wide coverage of five countries (Germany, Greece, Switzerland, Italy, and the UK), four seasons, and both daytime and nighttime coverage. The survey campaign from Arizona State University, Tempe, Arizona, U.S. is a unique data set to test our model in very hot conditions with a maximum air temperature of 42.9°C and a maximum MRT of 85.7°C; conditions that are at the edge and even outside our fitting ranges. For benchmarking purposes, we also tested the original local TSV equations developed from the RUROS data set, that is, the first seven equations in Table 2, and the other global TSV model, Global Outdoor Comfort Index (GOCI) (Salata et al., 2016). The GOCI model still uses constant coefficients (i.e., capturing the linear relationship between meteorology and TSV), but includes many other factors (e.g., latitude, mean annual temperature, mean temperatures of the hottest and coldest months) for global application. The original scales of our TSV metamodel and GOCI are both 9-point scales (+4 to −4), but here we normalize their outputs to a 5-point scale (+2 to −2) that the RUROS data set uses.

In Figure 4a, we show the comparison between predicted TSV (by three approaches) against observation, aggregated for each group (country, season, daytime/nighttime). For the RUROS data set, our new climate-adaptive TSV metamodel can achieve equivalent performance ($RMSE = 0.84$) as the seven local TSV equations ($RMSE = 0.83$), and better performance than the GOCI model ($RMSE = 0.95$) that has a systematic bias to overestimate TSV. Note that the RUROS data set has been used to develop the seven local TSV equations, but has not been directly used for our TSV model or GOCI training; instead, both GOCI and our TSV model ingested the coefficients of seven local TSV equations for model development. For the ASU data set, our TSV model can satisfactorily reproduce observations with an $RMSE$ of 0.68, still better than the GOCI model ($RMSE = 0.77$). The two test data sets span wider ranges of meteorological conditions ($T = -4.3$ – 42.9°C ; $H = 14$ – 98% ; $W = 0$ – 5.4 m/s; $R = 1.1$ – 85.7°C) than those used for TSV metamodel development ($T = 8.3$ – 32.6°C ; $H = 16$ – 81% ; $W = 0.2$ – 2.2 m/s; $R = 9.2$ – 41.1°C ; see average values in Table 2). The agreement between predicted and observed TSVs across extended ranges (particularly the ASU test results) indicates that the statistical relationships encoded in the metamodel can reliably estimate human sensation across various meteorological conditions.

In Figure 4b, we present model performance in terms of RMSE and mean bias error (MBE) across daytime and nighttime periods and different seasons, with sample sizes indicated on the x-axis. The model yields comparable RMSE for summer nighttime (sample size = 417) and summer daytime (sample size = 2334), while both show very small MBE, indicating minimal systematic bias, particularly given the large meteorological data set for model application. We do not observe a clear seasonal pattern in RMSE; however, summer exhibits the smallest MBE, which is most relevant for our intended application. Further details on uncertainty quantification based on RMSE and MBE are provided in Section 3.5.

Compared to the pioneering attempt at developing a global TSV model (i.e., GOCI), the key contribution of our TSV metamodel is in capturing the nonlinear effects of meteorological variables and their interactions on thermal sensation, making it more climate-adaptive, especially for applications across many regions without in situ TSV data sets. Accurately reproducing subjective human thermal sensation remains challenging. Given that our model has already shown an equivalent performance compared to locally calibrated TSV equations, we note that the remaining precision limitations likely reflect the simplified, linear structure of many local TSV models, which may not fully capture the complex, nonlinear relationships between meteorological conditions and thermal sensation. In addition, beyond acclimatization, TSV equations/models will only characterize the relationship between meteorological variables and a typical population even at the city level; there are many factors (e.g., clothing, age, gender) at the individual level that cannot be explained by these equations/models.

3.2. Divergence Across Thermal Metrics, Explained by Meteorological Sensitivities

Based on the developed global TSV metamodel and seven selected HSI, this section (a) examines how heat assessments from various thermal metrics would align with, or deviate from, each other, and then (b) attributes the divergence to the dissimilar sensitivities of these metrics to meteorological variables. For the first goal, we compute seven HSI and the new climate-adaptive TSV metamodel, under meteorological forcings drawn from a large global data set covering the 100 most populous cities in the world. In Figure 5a, we show the Pearson correlation coefficients (r_p) for each pair of metrics. Based on the Pearson correlation coefficients, we conducted a hierarchical clustering (implemented by MATLABTM's *linkage* function with the *average* method in the Statistics and Machine Learning Toolbox), which organizes items into a hierarchical structure, represented as a dendrogram (Figure 5b) where metrics that perform more similarly are connected at a lower level. For the second goal, we conduct MCMC subset simulations to unravel the sensitivities (indicated by SS) of each metric to meteorological variables (T : air temperature (°C); H : air relative humidity (%); W : wind speed (m/s); R : mean radiant temperature, MRT (°C)). In Figure 5c, we show the SS of eight thermal metrics to four meteorological variables at exceedance levels of 10%, that is, the 90th percentile or top 10% of summertime scenarios.

The correlation (Figure 5a) and clustering (Figure 5b) results classify the eight metrics into four groups: (a) *mPET*, *UTCI*, *SET*, and *AT*, collectively referred to as “human energy models” given their sophisticated representation of human energy balance processes; (b) *HI* and *WBGT*, referred to as “integrated weather indices” considering their wide adoption by weather services (though they are also supported by biophysical principles (Liljegren et al., 2008; Lu & Roms, 2022; R. G. Steadman, 1979)); (c) the thermal sensation metamodel (i.e., TSV), which has strong correlation with human energy models (group 1, $r_p = 0.85$ – 0.90), weaker correlation with integrated weather indices (group 2, $r_p = 0.68$ – 0.73), and very weak correlation with T_{wb} ($r_p = 0.39$); and (d) the wet-bulb temperature (T_{wb}) as an outlier, with relatively weak correlation ($r_p = 0.67$ – 0.83 , last row of Figure 5a) with all other HSI, except for *WBGT*.

Combining with the sensitivity analysis (Figure 5c), we can explain how differences in the influence of the four meteorological drivers on the HSI lead to alignment or disagreement among thermal metrics. The human energy models (*mPET*, *UTCI*, *SET*, and *AT*; first four rows in Figure 5c) are more responsive to changes in radiation and wind than to changes in humidity. In contrast, integrated weather indices (*WBGT* and *HI*, fifth and sixth rows in Figure 5c) show relatively higher sensitivities to humidity than human energy models. Even though *WBGT* also incorporates the four main meteorological variables, it exhibits lower sensitivities to wind and radiation than the four human energy models. The thermal sensation metamodel (TSV, seventh row in Figure 5c) is clearly distinguishable in its meteorological sensitivity from all thermodynamic stress metrics: it has a higher sensitivity to radiation and lower sensitivities to temperature and humidity, leading to the occurrence of unperceived stress scenarios that we detail in later sections. T_{wb} shows the highest sensitivity to humidity (much higher than *HI*, the only other metric i.e. also based solely on humidity and temperature), implying that it overemphasizes humid heat

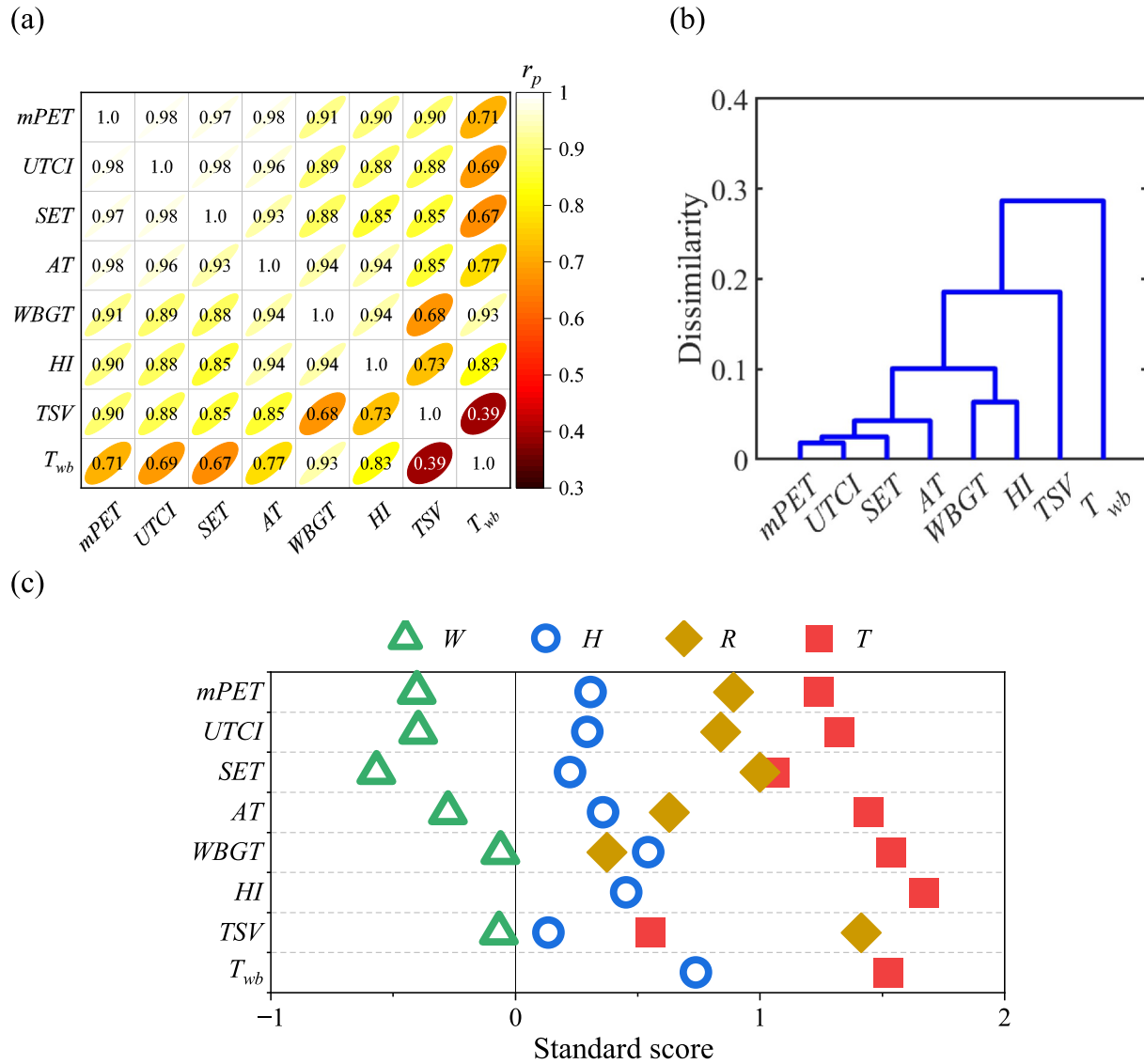


Figure 5. (a) Pearson coefficients (r_p) between all pairs of thermal metrics; (b) dendrogram via hierarchical clustering; and (c) standard scores (SS) for meteorological variables of the eight thermal metrics at exceedance levels of 10%. Tests in (a, b) are based on real-world meteorological conditions; test in (c) is based on MCMC simulations; all meteorological forcings are based on three summer months over 10 years (2010–2019) in 100 global cities.

extremes and the potentially adverse humidifying effects of green and blue infrastructure on human thermal stress more than other thermal metrics.

Based on the clustering and sensitivity results, a separation of spatiotemporal scales for the various HSI emerges, and provides guidance for application-specific heat evaluation frameworks. Human energy models ($mPET$, $UTCI$, SET , and AT) account for all meteorological drivers of thermal stress, particularly with higher sensitivities to wind and radiation, which vary at much finer spatiotemporal scales than air temperature and humidity. This makes them ideally suited for studies at fine temporal (e.g., sub-daily) and spatial (e.g., street-to-neighborhood) scales, particularly in urban settings where complex surface morphologies create high spatial variability even over short periods or distances. In contrast, integrated weather indices ($WBGT$ and HI), with higher sensitivities to temperature and humidity, may be more effective for studies with coarse temporal (e.g., weekly to annual) and spatial (e.g., city to global) scales, especially in detecting humid heat extremes since temperature and humidity are largely shaped by synoptic patterns (e.g., blocking high-pressure systems, atmospheric rivers, and moisture advection from water bodies). Furthermore, we emphasize that T_{wb} should be interpreted as a thermodynamic

upper limit that delineates where humans simply cannot survive (Buzan & Huber, 2020), as it was originally defined (Sherwood & Huber, 2010), instead of an assessment tool for HHWS. This distinction is particularly important given the mismatch between its underlying definition (a fully wetted surface with a high evaporation rate unconstrained by aerodynamic mixing limitations) and realistic human body conditions, as well as its relatively vague thermal stress category classification.

3.3. Spatiotemporal Hotspots for Sensation-Stress Metric Divergence

We now focus on heat conditions under which assessments from human thermal sensation models deviate from those of HSI. We selected the most widely used HSI from each clustering group (i.e., UTCI from human energy models and WBGT from integrated weather services) and defined “stress scenarios” when UTCI or WBGT exceeds its own threshold. Specifically, for UTCI, we adopted 26°C as a warning threshold, which is the lower limit of the moderate heat stress category (Bröde et al., 2012) and the point at which UTCI-mortality U-shaped curves become steeper (Di Napoli et al., 2018), indicating an increase in heat health risk. For WBGT, we adopted 25°C as a warning threshold; it is also the lower limit of the moderate heat stress category in some classifications (ECMWF, 2021; MEG, 2021; Parsons, 2006) and the threshold of applying exposure limits and resting schedules as suggested by ISO (2017), ACGIH (1996), NIOSH (2016), and OSHA (2011). Then, we defined “unperceived stress scenarios” as the cases when either UTCI or WBGT indicates heat stress (i.e., HHWS, if available, would release heat alerts) but TSV does not signal a heat sensation, that is, $(UTCI > 26^{\circ}\text{C OR WBGT} > 25^{\circ}\text{C}) \text{ AND } (TSV \leq 0)$. The practical meaning of such “unperceived stress scenarios” is that individuals may not feel the heat threat, and have to be advised by HHWS to take timely behavioral adaptation. The robustness of our conclusions with respect to these thresholds will be reviewed later (Section 3.5). More critically, the notion of an “unperceived stress scenario” presupposes that HSI are better indicators of actual clinical outcomes than TSV. Indeed, there is evidence in the literature that mortality and morbidity are well predicted by HSI, for example, UTCI and WBGT (Di Napoli et al., 2018; Guo et al., 2024); while the link between TSV and heat-health outcomes is much less established. In addition, considering HHWS based on HSI currently remain the most feasible and operational tools for predicting and communicating heat-related risks, a decoupling between thermosensory perception and the body's actual thermodynamic response may itself pose a risk by reducing appropriate behavioral adaptation in the absence of HHWS information.

In Figure 6, we show the spatiotemporal patterns of unperceived stress scenarios using two approaches: (a) for 17 cities using their own 17 original local TSV equations collected from meta-analysis (denoted with ** in Table 2) (left panel); (b) for 100 cities worldwide using the developed climate-adaptive TSV model (right panel). Specifically, in Figure 6a, we show the unperceived stress/stress periods percentages for all cities evaluated via approach 1 or 2, while in Figure 6b, we show the zoom-in panels for critical cities with high unperceived stress/stress periods percentages (top 5 and top 10 cities for Figures 6b1 and 6b2, respectively). In Figure 6c, we show city-averaged diurnal profiles of stress/total periods (red), unperceived stress/stress periods (gray), and unperceived stress/total periods (blue) percentages.

From a spatial perspective, low-latitude coastal Asian cities show higher unperceived stress percentages than other cities (Figure 6a). Figure 6b1 highlights the top 5 cities, which are all Asian, from the 17-cities results: Singapore, Hong Kong, Changsha, Wuhan, and Guangzhou. The 100-cities results using the TSV meta-model (Figure 6b2) offer a concurring but more complete picture, by including more South (Surat, Chattogram, Dhaka, and Karachi) and Southeastern (Yangon and Ho Chi Minh City) cities for which local TSV equations are not available. In addition to these Asian cities, some hot-humid coastal cities (e.g., Miami, Houston, Dar es Salaam, Luanda, Lagos) also have relatively high unperceived stress percentages, but percentages remain lower than 20% of the stress periods. From a temporal perspective, we found that unperceived stress scenarios occur far more frequently at nighttime (roughly before 8a.m. and after 6p.m.; Figure 6c), implying that sensation and stress are more likely to decouple at nighttime. The reasons for these spatiotemporal hotspots are explained by a sensitivity analysis and meteorological statistics in Section 3.4.

From a model-precision perspective, our findings on the spatial (low-latitude coastal Asian cities) and temporal (nighttime) patterns are identical when using local TSV equations or the global TSV model. Several cities are covered by both the local- and global-TSV tests and show consistent patterns: Rome and Tehran both show less than 1% unperceived stress percentages, while Singapore, Hong Kong, Changsha, Wuhan, and Guangzhou show higher unperceived stress percentages (>10%) in both tests, with consistently higher percentages appearing in the

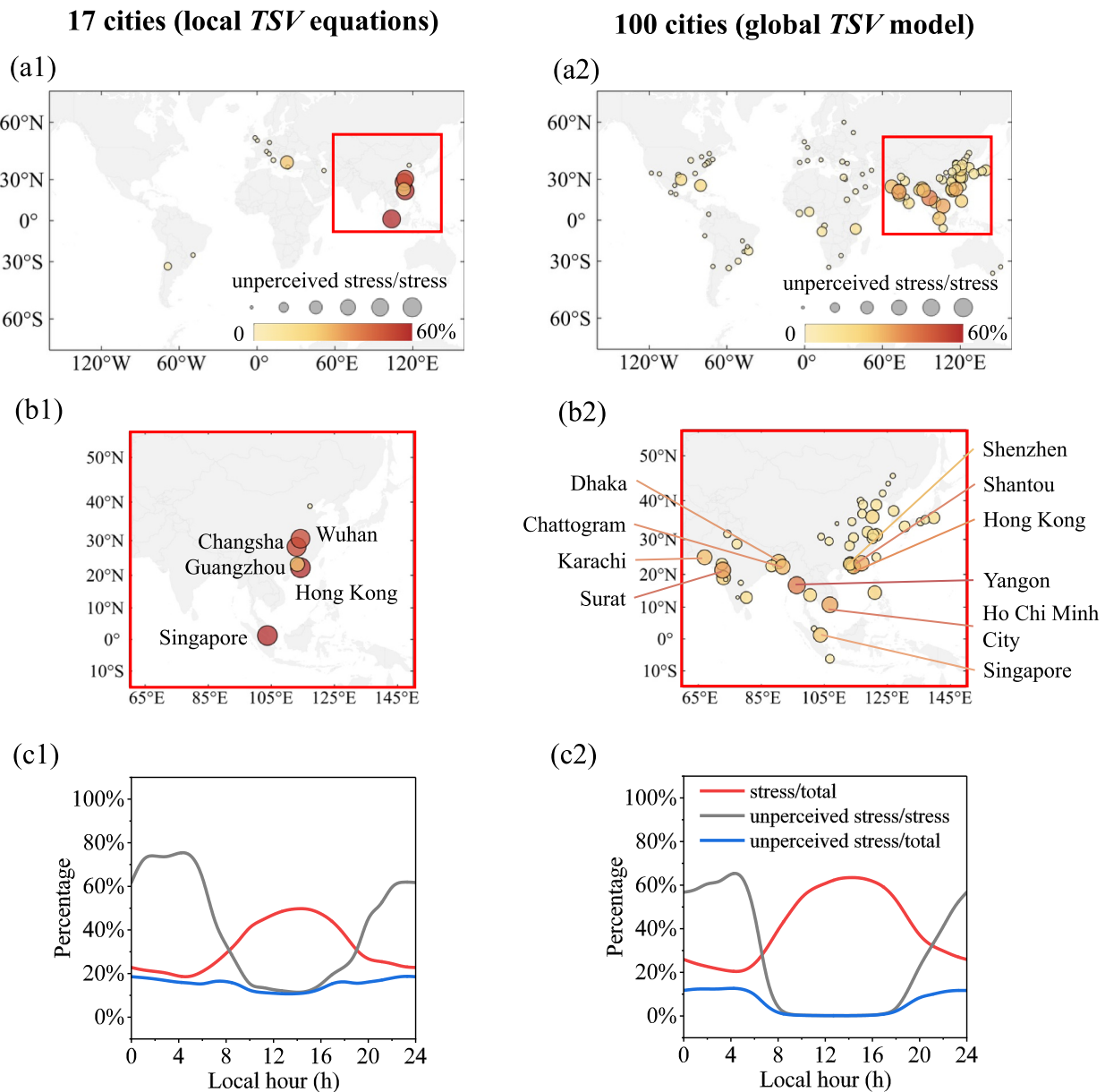


Figure 6. (a) Unperceived stress/stress percentages for test cities with (b) zoom-in panels highlighting critical cities with higher unperceived stress/stress percentages. Circle size and color both indicate daily averaged unperceived stress/stress percentages, with larger and darker circles denoting higher percentages. (c) City-averaged diurnal profiles of stress/total percentage (red), unperceived stress/stress percentage (gray), and unperceived stress/total percentage (blue). Panels (a1–c1) show data from 17 cities evaluated by their own original local TSV equations that are available from previous studies (denoted by ** in Table 2). Panels (a2–c2) show data from 100 cities worldwide evaluated with the global TSV metamodel developed in this study (Equation 3).

local TSV tests. The large divergence when using the local TSV equations is expected because in situ TSV surveys and subsequent development of city-specific TSV equations capture thermal acclimatization to a greater degree compared to a globally applicable model. That is, local populations in hotter climates are used to extreme heat and are less likely to perceive it as a nuisance, which then implies that they are less likely to take behavioral measures to reduce their heat exposure.

3.4. Meteorological Drivers of Diverging Stress and Sensation Metrics

Given the observed discrepancy between heat stress and sensation metrics, we now (a) illustrate the meteorological conditions that cause stress-sensation divergence; and (b) explain the mechanisms behind this divergence

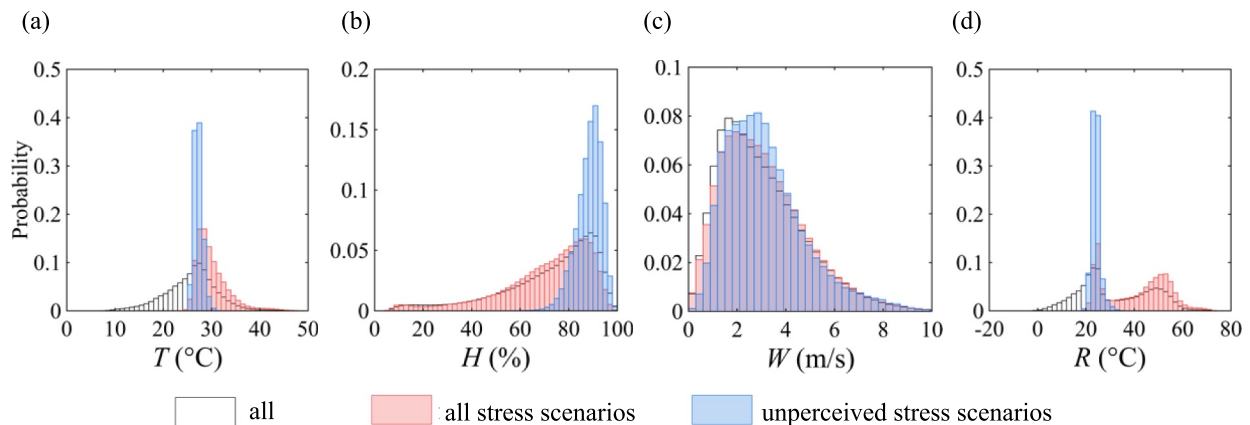


Figure 7. Probability distributions of each meteorological variable under all (white), all stress (red), and unperceived stress (blue) scenarios. Meteorological variables: (a) T : air temperature ($^{\circ}\text{C}$); (b) H : air relative humidity (%); (c) W : wind speed (m/s); (d) R : mean radiant temperature ($^{\circ}\text{C}$).

by linking observed conditions to model sensitivity test results. In Figure 7, we depict the probability distributions of meteorological variables under all scenarios (white), all stress scenarios (red), and unperceived stress scenarios (blue) for the 100-cities global-TSV results.

The climate signature of unperceived stress scenarios corresponds to a certain type of heat stress—nocturnal humid heat stress, characterized by a combination of moderately high air temperature ($T = 25\text{--}30^{\circ}\text{C}$; Figure 7a), very high air humidity ($H = 80\%\text{--}100\%$; Figure 7b), and moderately high mean radiant temperature ($R = 20\text{--}30^{\circ}\text{C}$; Figure 7d). Recall that in Figure 5c, we found TSV is more responsive to radiation, and less responsive to air temperature and humidity, compared with other stress metrics. This explains why the unperceived stress scenario is predominantly a nighttime phenomenon (when the absence of strong solar radiation dampens human heat sensation) and more prevalent in low-latitude coastal Asian cities (where persistent marine moisture advection, oceanic thermal inertia, and sea-land-breeze dynamics allow elevated temperature and humidity to persist at night).

3.5. Discussion and Uncertainty Quantification

One of the main outcomes of this paper is the identification of spatiotemporal hotspots of unperceived stress scenarios and their association with certain climatic heat stress attributes. Particularly, with the development of a climate-adaptive global TSV model, we are able to pinpoint the global cities (even those without a local TSV study) where the populations are most at risk from unperceived heat risks, and where targeted HHWS are needed. Accurately estimating the unperceived stress percentages in data-scarce regions remains challenging, but we have quantified uncertainties from several sources and confirmed that our spatiotemporal conclusions are robust:

1. Uncertainty raised from the developed global TSV metamodel: in addition to testing unperceived stress scenarios with both global and local TSV models, we conducted two additional tests. First, we did a bias correction (BC): for every predicted TSV value, we subtracted the MBE (see Figure 4b, values doubled for 9-point TSV scale) before applying the $\text{TSV} < 0$ indicator. We report the bias-corrected percentages in Figure S2 in Supporting Information S1 (blue columns). Second, we utilized the Monte Carlo (MC) results to decompose RMSE into systematic bias (MBE) and random error (σ), that is, $\text{RMSE}^2 = \text{MBE}^2 + \sigma^2$. Then we generated normal distributions of random errors $\varepsilon_i \sim N(\text{MBE}, \sigma^2)$ for each hour in each city, computed a perturbed TSV ($\text{TSV}_{\text{perturbed}_i} = \text{TSV}_{\text{predicted}_i} - \varepsilon_i$), counted how many perturbed values fall below zero (unperceived), and then repeated this process 1,000 times. We report the median and the 2.5–97.5 percentile credible interval (95% CI) of perturbed percentages in Figure S2 in Supporting Information S1 (orange columns). We found both spatial (Figure S2a in Supporting Information S1) and temporal (Figure S2b in Supporting Information S1) patterns hold robust: in Figure S2a in Supporting Information S1, all original top-10 cities remain in the BC top-10 (BC: ✓ for all), and 8 of 10 remain in the MC top-10 (MC: ✓); while the other 2 cities are replaced by near-neighbors (Mumbai, Kolkata) from the same South/Southeast Asian cluster, reflecting shuffling within a densely packed group rather than any structural change. In Figure S2b in Supporting Information S1, the strong nighttime tendency is preserved under both approaches, with a remarkably

small 95% CI. In addition, we conducted a leave-one-region-out test to see how the model performs when extrapolating to cities that are not included in model development. We exclude Asian cities (Hong Kong, Changsha, Singapore, Wuhan, Guangzhou, Tianjin) in collected TSV equations to fit a leave-Asian-cities-out TSV metamodel (Figure S3 in Supporting Information S1) and repeat spatiotemporal unperceived stress percentage analysis (Figure S4 in Supporting Information S1). We find that the leave-Asian-cities-out TSV model still reproduces the same spatiotemporal hotspots (Figures S4a1, S4b1, and S4c1 in Supporting Information S1) as the original local TSV equations do (Figures 6a1, 6b1, and 6c1). This agreement increases confidence in extrapolating the collected TSV-meteorology relationships to data-scarce regions. We also compare 100-city results (Figures S4a2, S4b2, and S4c2 in Supporting Information S1) with complete global TSV metamodel results (Figures 6a2, 6b2, and 6c2) and find the spatiotemporal patterns remain unchanged, while quantitative results (percentages) vary slightly.

2. Uncertainty raised from thermal stress/sensation thresholds: Figures S5 and S6 in Supporting Information S1 show that these patterns remain robust across alternative UTCI, WBGT, and TSV threshold definitions. As shown in Figures S5 and S6 in Supporting Information S1, we varied UTCI (27, 28, 29°C), WBGT (26, 27, 28°C), and TSV (0, 0.5, 1) thresholds used to define “unperceived stress scenarios.” We divided hours into daytime (7 a.m.–7 p.m.) and nighttime (7 p.m.–7 a.m.) (Figure S5 in Supporting Information S1) and divided the 100 cities into top 20% cities (ranked by unperceived stress/stress percentages with base/default thresholds) and bottom 80% cities (Figure S6 in Supporting Information S1); and calculated the unperceived stress/stress percentages for each group. The results show that our conclusions on the temporal (nighttime > daytime) and spatial (top 20% cities > other 80% cities) remain accurate for almost all threshold scenarios. Further investigation of uncertainties/caveats associated with the developed global TSV model is provided in the Conclusions.

4. Conclusions

This study advances guidance of heat assessments and supports effective behavioral adaptation from two complementary perspectives: (a) For HHWS that are based on HSI, divergent heat assessments across different HSI can be puzzling and problematic in practice. We showed that such divergence is systematically linked to contrasting sensitivities of HSI to meteorological drivers, and developed a clustering framework to guide HSI application while accounting for their meteorological sensitivities and characteristic spatiotemporal scales. (b) For subjective human heat sensation that can be quantified by the TSV, we uncovered where, when, and why it diverges from HSI-based assessments, and examined the underexplored implications of such divergence. Our analysis identified the conditions (specifically, nighttime humid heat stress in low-latitude coastal Asian cities) under which these two types of metrics are more likely to diverge, highlighting situations where sole reliance on sensation may be inadequate.

Considering the extensive epidemiological evidence proving that UTCI and WBGT (and other HSI) are robustly associated with heat health outcomes (e.g., mortality and hospital admissions (Guo et al., 2024; Pantavou et al., 2025; Spangler et al., 2023; Urban et al., 2021)), we emphasize that where, when, and among whom perceived heat may be lower than indicated by HSI warrants careful attention and targeted responses. From a spatial perspective, most Asian cities with high unperceived stress percentages are densely populated (e.g., the top 10 cities house 82 million people (United Nations, 2019)) and in developing regions, thus if heat risks exist but are not perceived by individuals, the health outcomes of prolonged heat exposure could be severe. From a temporal perspective, while the hours prone to sensation-stress divergence are dominantly during the nighttime, they also cover early morning and early evening (this is particularly true with the 17-cities local-TSV results; see two peaks of the blue curve in Figure 6c1). These are periods when urban residents are engaging in commuting and outdoor leisure activities, and when outdoor workers may perform strenuous labor under a shifted work schedule to avoid daytime heat exposure (Morabito et al., 2020; Takakura et al., 2018).

Here, it is important to recognize that the results of prolonged heat exposure are related to individual vulnerability, which can be collectively shaped by biophysical and socioeconomic factors. For example, older adults are found to be less sensitive to heat stimuli than younger ones (Younes et al., 2023), implying that they are more prone to exposing themselves to heat stress that their bodies cannot tolerate or adapt to. On the other hand, air-conditioning penetration is higher in high-income neighborhoods with newer housing. In this case, indoor air-conditioned environments can distort the translation of outdoor thermal risks assessed here to actual indoor exposure. Lower-income populations may experience indoor heat stress levels comparable to, or even exceeding, those

outdoors (Agarwal et al., 2024; Uejio et al., 2011), thus extending the exposure time and increasing risk. Targeted real-time heat monitoring is needed for these vulnerable places, periods, and populations; for example, one solution could be personalized heat strain monitoring for outdoor workers that alerts them to their actual heat strain levels through the rapidly expanding wearable health monitoring technologies (Cannady et al., 2024).

Our results can inform heat assessment and adaptation across a wide range of research and policy domains. For climatologists and meteorologists, we demonstrate the potential bias of using a single HSI to represent specific heat hazards, and show that divergence among HSI can be systematically explained by their contrasting sensitivities to key meteorological drivers, underscoring the need to select HSI consistent with the spatiotemporal scale of the research objective. For public health researchers and epidemiologists, our findings highlight the importance of identifying which metrics best predict heat-related health outcomes across regions: we regard HHWS based on HSI as a key intervention for addressing unperceived heat stress, given the widespread implementation and the well-established links between HSI and health outcomes. At the same time, our TSV analysis emphasizes the role of local thermal acclimatization, whose influence on actual health outcomes remains insufficiently understood. Therefore, the clinical implications of sensation-stress decoupling require more targeted observational studies. Understanding whether and how the unperceived heat stress we report here may help explain emerging evidence of the critical importance of nighttime for heat-related mortality in Asian countries (He et al., 2022; Kim et al., 2023). This highlights the value of additional epidemiological evidence on TSV-health relationships, particularly for vulnerable subgroups (e.g., older adults and outdoor workers), as a basis for incorporating TSV-informed metrics into future HHWS. For policymakers, given the strong epidemiological links between thermodynamic HSI and adverse health outcomes, the identified divergence between thermal sensation (TSV) and thermodynamic HSI reveals a critical risk context in which individuals may not recognize danger, calling for targeted HHWS and timely interventions that do not rely on heat perception alone. We should also caution that local adaptation cannot be assumed to be stable or sufficient, particularly under rapidly changing climatic conditions and during extreme events such as heatwaves. Acclimatization processes may be challenged when environmental conditions exceed historically experienced ranges, or when exposure patterns shift (e.g., warmer nights, higher humidity, prolonged events). In such contexts, the decoupling between perceived comfort and physiological strain becomes especially relevant from a risk perspective.

Finally, we conclude by outlining future research needs to address limitations of the present study. The primary goal of our analysis on sensation-stress divergence is to identify its spatiotemporal hotspots and explain its causal mechanisms. A precise quantification of the level of unperceived stress conditions remains challenging due to (a) a lack of a global HHWS standard with region-specific HSI thresholds based on region-specific epidemiological studies, and (b) the limited and geographically uneven TSV survey data coverage at a global scale. While these are major research gaps beyond the scope of this study, we tested the uncertainty they inject into our results, and the robustness of our conclusions (Section 3.5). Future research could enhance the global TSV model through improved modeling techniques (e.g., logistic regression) and expanded data sources; on the other hand, our climate-adaptive TSV model offers a framework to incorporate future TSV survey data, which may grow rapidly with advances in wearable health monitoring technologies and facilitate future TSV model development (Parchami et al., 2025).

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The ERA5 hourly data for air temperature, humidity, and wind speeds are available at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels?tab=overview>. The ERA5-HEAT hourly data for mean radiant temperature are available at <https://cds.climate.copernicus.eu/datasets/derived-utci-historical?tab=overview>. The statistics used to select the 100 most populous cities are available at <https://population.un.org/wup/assets/Download/Archive/WUP2018-Excel-files.zip>. Data and codes used in all the figures can be accessed via a public Figshare repository (Huang, 2026).

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