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Authors
Deshpande, Aniruddha
Scovronick, Noah
Clasen, Thomas
et al.

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Heat Exposure among Adult Women in Rural Tamil Nadu, India

Aniruddha Deshpande, Noah Scovronick,* Thomas F. Clasen, Lance Waller, Jiantong Wang, Vigneswari Aravindalochanan, Kalpana Balakrishnan, Naveen Puttaswamy, Jennifer Peel, and Ajay Pillarisetti*

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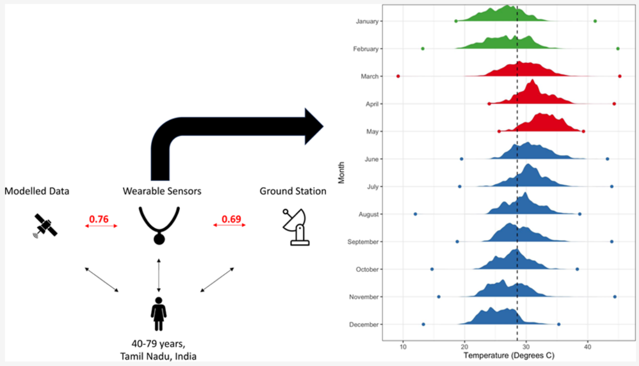
ABSTRACT: Exposure to heat is associated with a substantial burden of disease and is an emerging issue in the context of climate change. Heat is of particular concern in India, which is one of the world's hottest countries and also most populous, where relatively little is known about personal heat exposure, particularly in rural areas. Here, we leverage data collected as part of a randomized controlled trial to describe personal temperature exposures of adult women (40−79 years of age) in rural Tamil Nadu. We also characterize measurement error in heat exposure assessment by comparing personal exposure measurements to the nearest ambient monitoring stations and to commonly used modeled temperature data products. We find that temperatures differ across individuals in the same area on the same day, sometimes by more than 5 °C within the same hour, and that some individuals experience sharp increases in heat exposure in the early morning or evening, potentially a result of cooking with solid fuels. We find somewhat stronger correlations between the personal exposure measurements and the modeled products than with ambient monitors. We did not find evidence of systematic biases, which indicates that adjusting for discrepancies between different exposure measurement methods is not straightforward.



KEYWORDS: *India, heat, temperature, exposure assessment, personal monitoring*

■ INTRODUCTION

Exposure to hot temperatures is a top environmental risk factor for global mortality.[1,2] In 2019, an estimated 308 000 deaths were attributed to heat exposure;[3] this already substantial burden is expected to increase as the climate continues to warm.[4] Heat is also associated with a substantial morbidity burden, as well as with reductions in labor productivity.[5] Heat exposure is of particular concern in India—a hot country and also the world's most populous[6]—where a large fraction of the population works outdoors, lives in dwellings that are thermally inefficient, and is unable to access cooling technologies such as fans or air conditioners.[7]

Despite these concerns, relatively little is known about personal exposure to ambient temperatures in India, particularly in rural areas. Ambient monitoring stations are sparse and even where present may not accurately represent individual exposures, as people frequently move between indoor and outdoor environments, both in the sun and in the shade. Improving exposure assessment for temperature can enhance our understanding of the health effects of heat and cold by reducing potential biases and measurement errors associated with ambient monitors and modeled products, which are commonly used in epidemiological and burden of disease studies.[1,8,9] Personal measurements may also highlight opportunities for intervention by identifying high-exposure activities.

In this study, we leverage data collected as part of the Household Air Pollution Intervention Network (HAPIN) randomized controlled trial of cookstove replacement to describe personal temperature exposures of adult women in rural Indian villages in Tamil Nadu. In addition, we compare personal exposure measurements to the nearest identified ambient monitoring stations, as well as to two sources of modeled temperature data often used in health effect studies (due in part to the limited spatial coverage of the ambient monitoring network).[8] Through these comparisons, we assess potential measurement errors when using proxies for personal temperature exposure.

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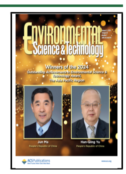

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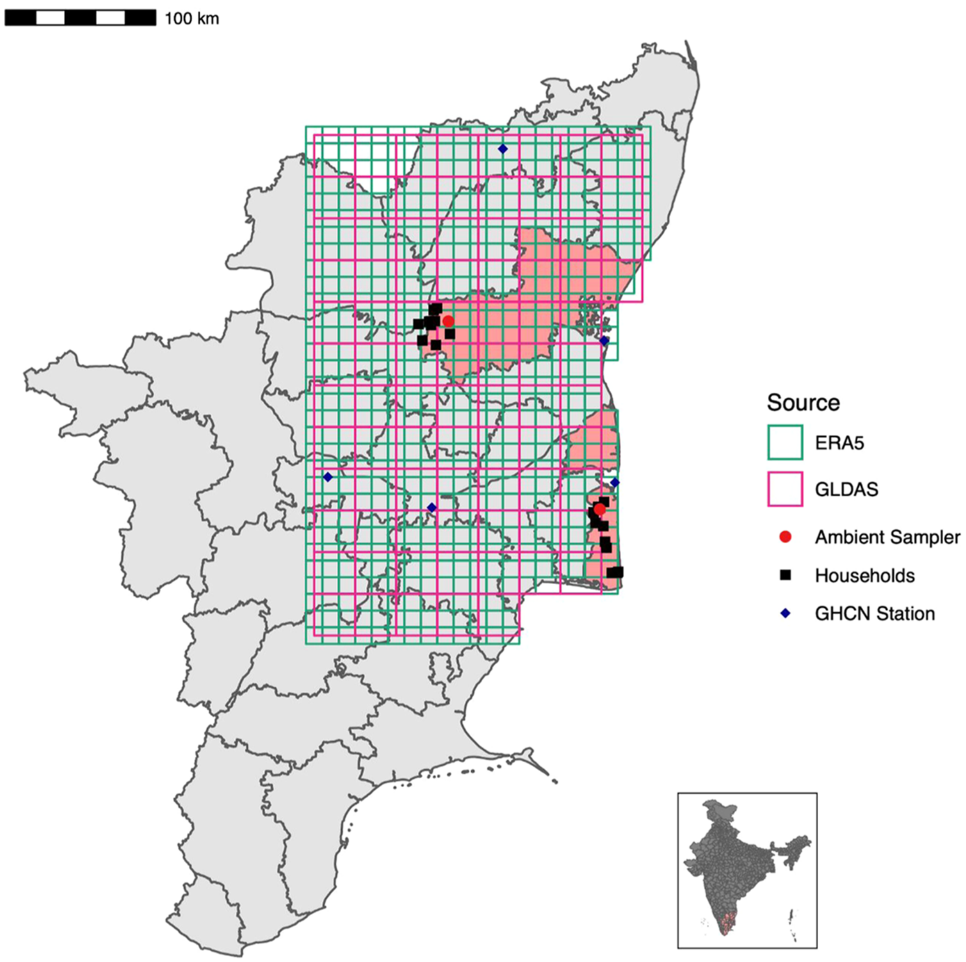

Figure 1. Map of the study villages and ambient monitors overlaid with grids from the two modeled temperature products. The districts of Villupuram (to the north) and Nagapattinam are shaded in pink.

■ METHODS

HAPIN Trial: Overview, Study Site, and Data Collection. The HAPIN multicountry randomized controlled trial (RCT) evaluated the effect of a liquefied petroleum gas stove and fuel intervention during pregnancy on birth weight, growth, and severe pneumonia in children and on blood pressure among adult women (40−79 years of age). The trial's research sites are in four diverse low- and middle-income settings: Guatemala, India, Rwanda, and Peru. The study began in 2017; the analysis of trial findings is ongoing. Details of the HAPIN trial have been published elsewhere.[10,11] The trial is registered with ClinicalTrials.gov (Identifier NCT029446282).

Here, we focus exclusively on non-pregnant adult women participants from the Indian site of the HAPIN trial, which consists of two districts, Villupuram, and Nagapattinam, in Tamil Nadu (Figure 1). The hilly Villupuram study site is located at an altitude of approximately 800 m above the sea level, while the Nagapattinam site, a coastal area, is located at an average elevation between 10 and 50 m above the sea level (full details on the sites, and how they were selected, are in Sambandam et al.[12]).

As part of the trial, participants were asked to wear a vest holding an Enhanced Children's MicroPEM (ECM, RTI International, North Carolina), a robust, lightweight, and validated nephelometric and gravimetric $PM_{2.5}$ monitor. Vests were codesigned with community members to minimize discomfort from wearing devices while also ensuring that samplers were properly oriented and placed.[10] The ECM weighs approximately 150 g and is capable of operating continuously for up to 48 h. These instruments measure temperature and humidity to correct real-time estimates of air pollution levels; here, we take advantage of these measurements as a representative of temperatures experienced by participants as they move through space and time. Temperature is logged every 30 s. Participants were asked to wear the vest while awake during the day and to hang the vest nearby when it is not being worn (such as while bathing or sleeping). The study evaluated exposures for 24 h periods on at least three occasions for each participant over the course of the 18-month HAPIN follow-up period.

HAPIN Ambient Monitors. In addition to personal exposure assessment, two ambient $PM_{2.5}$ monitors (Met One E-Sampler, Grants Pass, Oregon) were installed in the HAPIN study districts in Tamil Nadu to measure outdoor particulate air pollution (Figure 1). They also log meteorological parameters at 5 min resolution. We use these monitors, which we refer to as "HAPIN ambient monitors," as one point of comparison with personal monitors.

GHCN Ambient Monitoring Stations. As a second point of comparison with personal monitors, we obtained daily contemporaneous temperature measurements from the nearest established ambient monitoring stations available from the archive of the Global Historical Climatology Network

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(GHCN), accessed via the US National Oceanographic and Atmospheric Administration's National Centers for Environmental Information. The data were extracted by using the R package *rnoaa*. The locations of the stations relative to the study locations can be found in Figure 1.

Modeled Temperature Data. As a final point of comparison, we extracted contemporaneous temperature estimates from two modeled data products. The first is the ERA5-LAND product, which is a high-resolution (9 km) reanalysis data set based on the H-TESSEL land surface model.[13] The data set provides hourly estimates at 2 m above the land surface. ERA-5 data have been increasingly used in health effect studies.[1,9,14] The second product is NASA's GLDAS-2 product,[15] which provides temperature estimates every 3 h at a spatial resolution of 0.25 × 0.25°, a scale coarser than ERA-5 (Figure 1). GLDAS generates its estimates by fusing satellite- and ground-based observational data products, using advanced land surface modeling and data assimilation techniques.[15]

Data Analysis. First, we calculated descriptive statistics summarizing the personal exposure measurements by month and season, including mean temperature across all measurements, empirical distributions by month, and minima and maxima. Next, we assessed the correlation between personal exposures and corresponding estimates from the alternate data sources. For comparison with the temperatures measured by HAPIN ambient monitors, we matched all observations in each district to the closest corresponding station. To identify the closest GHCN station by Euclidean distance, we utilized the *rnoaa* R package. Finally, for comparison with the two modeled products (ERA5 and GLDAS), we used the GPS coordinates of each participant's block of residence to assign the relevant grid square. All correlations are based on daily average exposures, as the different data sources provide measurements at varying temporal resolutions.

In order to further summarize the differences between the personal measurements and the alternate data sources, we produced Bland–Altman plots.[16] Bland–Altman plots characterize the agreement between two different data sources or measurement techniques, displaying the variance between the two measurements, the direction of any bias, and if or how the bias changes along the exposure (temperature) distribution. Bland–Altmann analyses provide associations between the bias and the average temperature for the measurement data being compared. This enables the assessment of the strength of agreement between two sources, similar to a correlation coefficient, and how agreement varies across the observed temperature distribution. All Bland–Altmann analyses were generated relative to the personal measurements, again using daily averages for consistency across data sources.

Analyses were performed in R version 4.1.3 (R Foundation for Statistical Computing, Vienna, Austria).

Ethics. The study protocol has been reviewed and approved by institutional review boards (IRBs) and Ethics Committees at Emory University (00089799), Johns Hopkins University (00007403), Sri Ramachandra Institute of Higher Education and Research (IEC-N1/16/JUL/54/49), the Indian Council of Medical Research—Health Ministry Screening Committee (5/8/4-30/(Env)/Indo-US/2016-NCD-I), Universidad del Valle de Guatemala (146-08-2016), Guatemalan Ministry of Health National Ethics Committee (11-2016), Asociación Benefica PRISMA (CE2981.17), the London School of Hygiene and Tropical Medicine (11664-5), the Rwandan National Ethics Committee (No. 357/RNEC/2018), and Washington University in St. Louis (201611159). The study has been registered with ClinicalTrials.gov (Identifier NCT02944682).

RESULTS

Personal Measurements. A total of 614 measurements (approximately 1.7 million data points) were recorded from 104 different participants, for an average of 5.9 times (SD 2.2, range 1–11) per participant. The first measurement was on 13 June 2018, and the last one available in this data set was recorded on 29 June 2021. The average age was 49 years (SD

Table 1. Baseline Characteristics of the Study Population

characteristics	(N = 104)	
participant characteristics		
age at screening		
mean (SD)	49.0	(6.5)
highest level of education		
no formal education or primary school incomplete	99	(95%)
primary school complete	5	(5%)
main occupation[a]		
agriculture	87	(84%)
household	10	(10%)
unemployed	7	(7%)
other	9	(9%)
household characteristics		
household size		
mean (SD)	4.4	(1.3)
roof type in the main home		
thatch	28	(27%)
concrete	28	(27%)
ceramic/fired tile	25	(24%)
other	23	(22%)
wall type in main home		
concrete	55	(53%)
mud	39	(38%)
other	10	(10%)
floor type in the main home[b]		
concrete	58	(56%)
mud	42	(40%)
other	6	(6%)
air cooler/air conditioner		
no	104	(100%)
time to take to go get water and come back (minutes)		
mean (SD)	34.2	(32.9)
categorical household food insecurity[c]		
none (0)	83	(80%)
mild (1–3)	17	(16%)
moderate/severe (4–8)	4	(4%)
baseline exposure		
primary fuel type		
wood	104	(100%)
primary heating source		
do not use heating	91	(88%)
traditional cookstove/three-stone fire	11	(11%)
other	2	(2%)

[a]Eight respondents reported more than one main occupation (7 indicated two occupations, while 1 indicated three). [b]Multiple materials may be reported for the same household, so households may appear more than once. [c]The Food Insecurity Experience Scale—Developed by the Food and Agriculture Organization of the United Nations, http://www.fao.org/3/as583e/as583e.pdf

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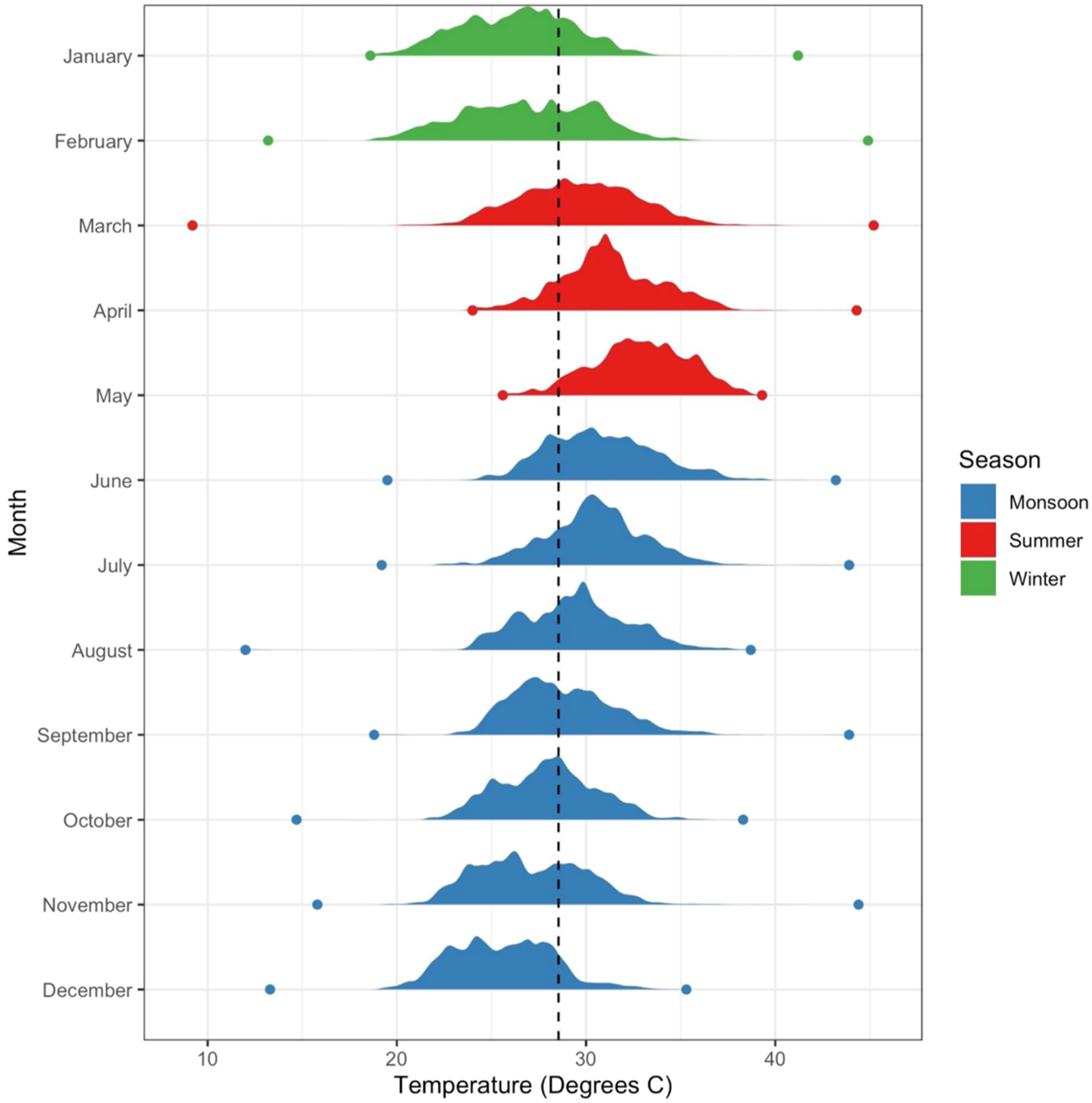

Figure 2. Density plots of personal exposure by month during the 2018−2021 study period. The vertical line indicates the average temperature over the study period. Dots are monthly average minimum and maximum values. Fill colors are seasons (blue is monsoon, red is summer, and green is winter).

= 6.5 years), most participants received little formal education, and most worked in agriculture (Table 1). House construction was a mix of traditional (e.g., thatch/ceramic/mud) and modern (e.g., concrete) materials, and no household had air conditioning.

The density functions of 30 s personal temperature exposure on the HAPIN participants by month for each of the three seasons (winter, summer, and monsoon) are reported in Figure 2. The overall average temperature exposure was 28.4 °C (SD 3.1), with seasonal differences; average exposure was 26.5 °C in winter (SD 2.9), 30.4 °C (SD 2.8) in summer, and 28.3 °C (SD 3.0) during the monsoon.

Figure 3 presents hourly personal exposures from multiple individuals for the same 24 h period, starting at 8:00 am on 25th November 2019. Two heat exposure-related features of interest in the study area are illustrated in this figure. First, temperatures differ across individuals on the same day, sometimes by more than 5 °C within the same hour. Second, the data suggests that some individuals experience sharp increases in heat exposure in the early morning or late afternoon/evening, potentially a result of cooking with solid fuels and, thus, proximity to stoves or other combustion sources (for example, for household heating). During these times, heat exposure for an individual can vary by several degrees within an hour.

Comparison of Exposure Sources. Summary statistics overall and by season for the different temperature sources are listed in Table 2. In general, the personal measurements tend to be intermediate between the lower temperatures reported by the modeled products and the slightly higher temperatures reported by the ambient monitors.

Scatterplots and correlations between personal exposures and alternate data sources are shown in Figure 4. Over the full study period, there were somewhat stronger correlations with the modeled products than with the semilocal ambient monitors. Correlations varied across seasons but were uniformly highest in the monsoon season and, with the exception of the HAPIN ambient sampler, were lowest in the summer. An analogous plot to Figure 4 but restricted to

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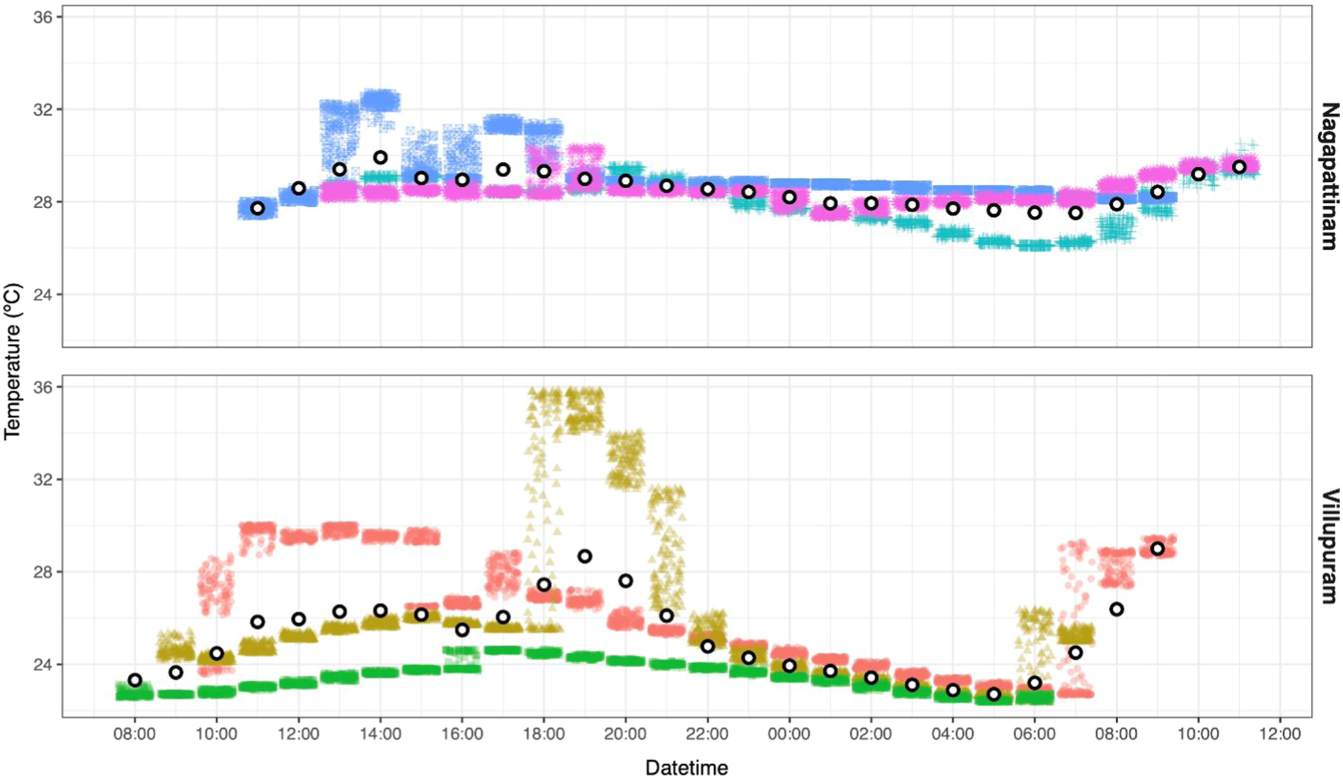

Figure 3. Personal exposure of six individuals (three in each district) from 8:00 am on 11/25/2019 to 8:00 am on 11/26/2019. Each individual is represented by a unique color-shape combination, and each small colored shape represents a single temperature measurement during a given hour. Points are slightly jittered to prevent overlap. White points with a black outline are average hourly measurements across all participants within a district.

Table 2. Daily Summary Statistics by Data Sources (Overall and by Season)

	all seasons		monsoon		summer		winter	
data source	mean (SD)	range	mean (SD)	range	mean (SD)	range	mean (SD)	range
HAPIN personal	28.4 (3.1)	19.6−36.3	28.3 (3.0)	20.1−36.3	30.4 (2.8)	22.4−36.3	26.5 (2.9)	19.6−32.8
HAPIN ambient	28.5 (3.2)	19.1−37.6	28.2 (3.1)	22.1−37.5	31.0 (3.8)	19.9−37.6	27.8 (2.6)	19.1−37.6
GHCN ambient	28.9 (2.7)	23.7−35.2	28.9 (2.7)	24.2−35.2	30.3 (2.0)	24.2−35.2	26.4 (1.3)	24.2−35.2
ERA5	25.4 (2.8)	19.5−32.5	25.2 (2.7)	19.6−32.1	27.7 (2.1)	19.6−32.1	23.8 (2.2)	19.5−27.9
GLDAS	25.3 (3.3)	18.0−34.6	25.2 (3.2)	18.1−33.7	28.0 (2.5)	22.2−34.6	23.2 (2.2)	18.4−28.5

extreme heat days (>35 °C) is reported in Supporting Information Figure S1.

The Bland−Altmann plots (Figure 5) indicate that the mean bias for both the ERA5-Land and GLDAS products was negative for the majority of the measurements in all seasons. In contrast, the distribution for the GHCN and HAPIN ambient sampler data is centered closer to zero, with a relatively even number of measurements with positive and negative biases. In the all-year analyses for all sources, slopes were ≤ ±0.21, indicating that the bias remained somewhat similar across the temperature distribution. Confidence bands were wider for the monitors compared to the modeled products, indicating more error. An analogous plot to Figure 5 but restricted to extreme heat days (>35 °C) is reported in Supporting Information Figure S2.

■ DISCUSSION

We have presented the results of opportunistic monitoring of personal temperature exposures in Tamil Nadu, India, which were collected as part of a large-scale household air pollution intervention study. To our knowledge, this is one of the very few studies of its kind in India, a country highly vulnerable to climate change and extreme heat, and the first conducted in multiple rural districts. We find that personal measurements follow expected seasonal trends but that even within a season or month, individuals experience a wide range of temperature exposure. The average exposure across the study period was 28.4 °C, but in all months, study participants experienced many exposures above 30−35 °C; exposures above 40 °C occurred in most months. We also found that differences of several degrees may be evident across individuals in the same district even within the same hour of the same day and that individuals themselves may have highly variable exposures within a short period of time. In some individuals, the daily pattern of heat exposure is suggestive of cooking or heating with solid fuels and other behaviors that likely impact exposure.

A previous study in peri-urban Telangana, India, compared personal measurements of temperature opportunistically collected from a similar monitor to the one employed in HAPIN with ambient measurements among a population of 50 participants.[17] They noted limited agreement between personal

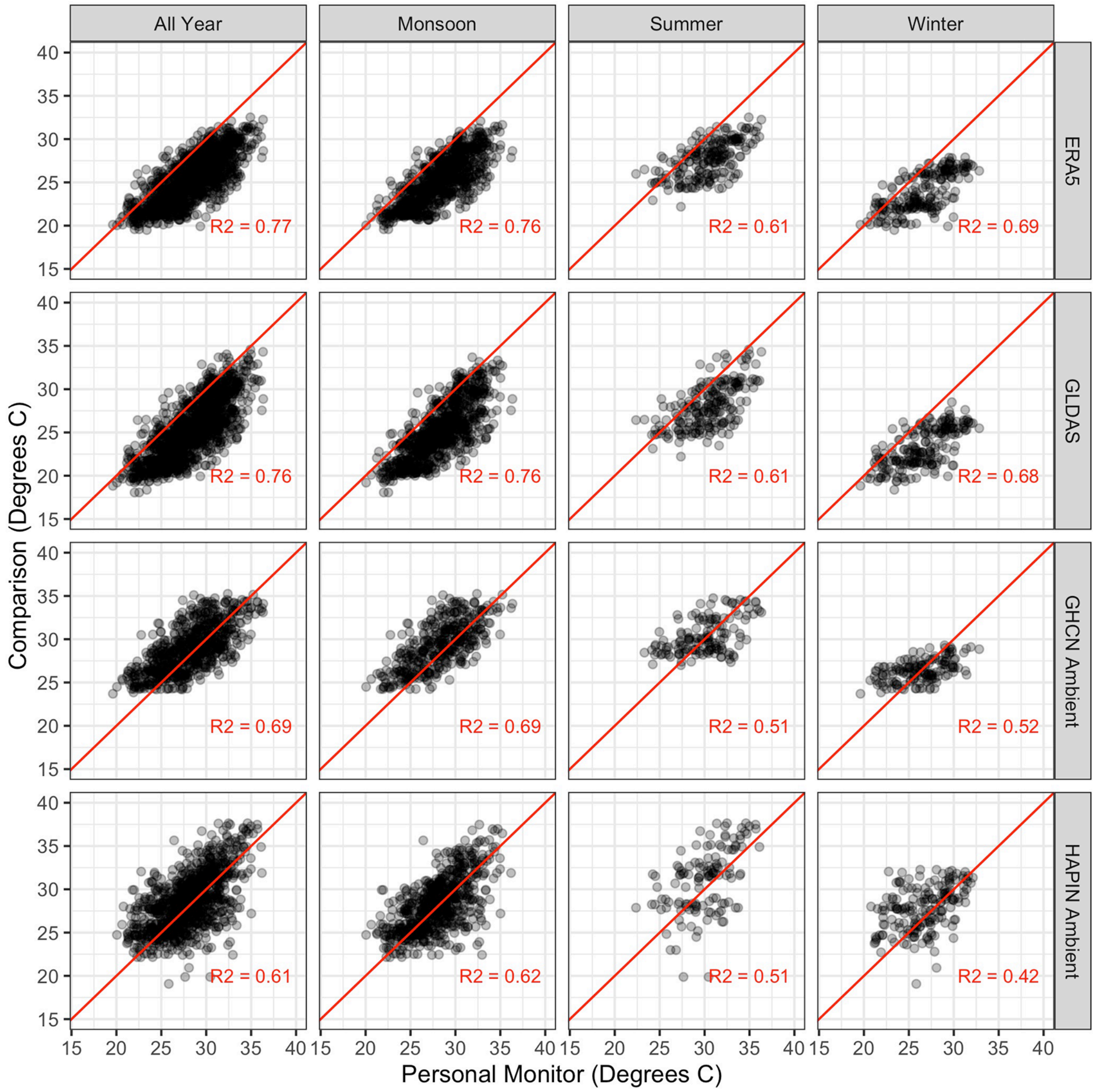

Figure 4. Scatterplots and simple correlations comparing personal exposures with ambient monitors and modeled products. Red lines are 1:1 lines; points represent daily average values.

and ambient samplers and suggested that additional factors, like altitude and demographic data, may help explain the discordance between the monitoring types. To the best of our knowledge, that study did not investigate relationships between modeled ambient temperature products and personal exposure as we did here.

We also compared our data from personal monitors with contemporaneous data from the study and government ambient monitors and two gridded meteorological products. In general, the modeled products performed best, having a higher correlation with the personal measurements and smaller mean errors, as shown in the Bland–Altman analyses. This information may be relevant in the choice of exposure data when conducting observational studies on the relationship between temperature and health (or nonhealth) outcomes. Nevertheless, differences were often ≥3–5 degrees in either direction, which may be problematic for the design of interventions to protect against extreme heat. The finding that there seemed to be no clear systematic relationship between the personal measurements and the alternative data sources indicates that adjusting for the discrepancies is not straightforward. The overall implication is that epidemiological studies based on existing options for exposure assessment may introduce exposure misclassification and therefore produce imprecise or inaccurate health effect estimates. Such misclassification could also affect the burden of disease calculations.

This study has several important limitations and raises the need for additional research. One key limitation is that we present data only for adult women, which may not be representative of the study population at large. Even within our population of adult women, more measurements would enhance the robustness of the results, particularly with respect to potential seasonality in correlations with the ambient monitors and modeled products. We also emphasize that the performance of these alternative sources of data in Tamil Nadu does not necessarily hold in other study locations, particularly those with more (and closer) monitoring stations. However, for many rural locations in low- and middle-income countries, we expect that similar discrepancies will be apparent. Additionally, we note that while our measured temperature exposures fell within expected bounds, further evaluation of the

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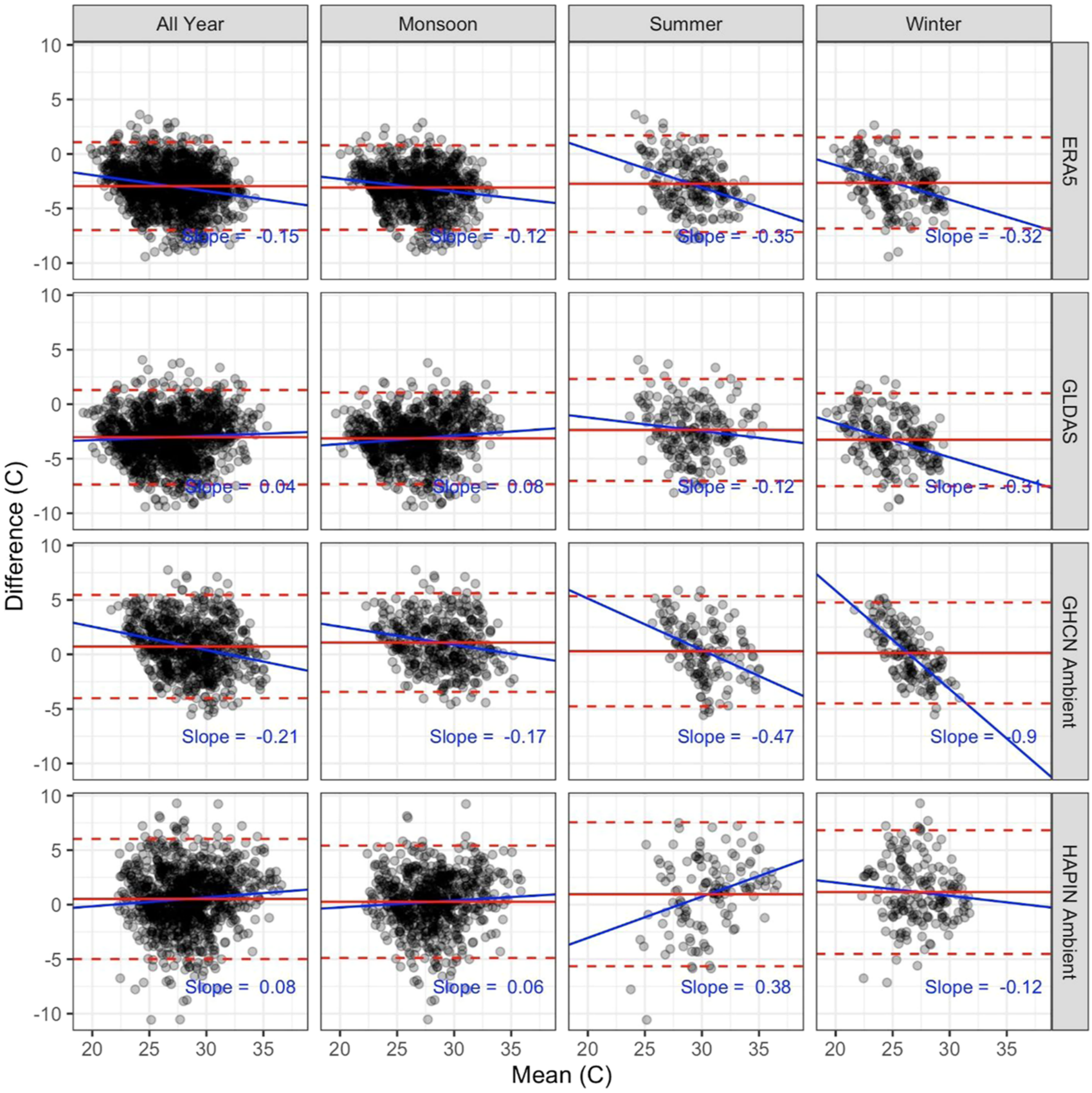

Figure 5. Bland−Altman plots comparing personal exposures with ambient monitors and modeled products. Blue sold lines are best-fit regression lines displaying the relationship between bias and mean changes in the daily temperature. Dashed red lines are 95% Wald confidence intervals; solid red lines are mean values.

use of these types of instruments as temperature monitors is warranted. Future work could compare the use of these opportunistic measures with other instrumentation, such as the well-validated temperature monitors used in occupational health assessments.

Future research can replicate these results with more data in other locations by exploring the drivers of differences between data sources and by explicitly analyzing how potential biases may influence epidemiological or econometric studies on the consequences of heat exposure. We believe that there are many opportunities to leverage existing data to answer these and other questions. Real-time particulate matter sensors have been used in hundreds of settings in dozens of contexts around the world to assess exposure to household air pollution arising from the use of solid fuels for cooking and heating. Because these real-time particulate matter monitors must measure temperature (and often also measure humidity), there is potentially a large amount of existing data that can be analyzed to characterize and describe heat exposures across a broad area of a typically unmonitored population. Furthermore, given the proliferation of these types of sensors around the globe, as part of primarily urban low-cost air monitoring networks, like the Purple Air network, there may be utility in assessing the information they provide on heat and humidity at a finer geographic and temporal scale. Such opportunistic monitoring may enable more advanced epidemiological analyses and provide a better estimation of personal temperature exposure.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.3c03461.

Figures showing correlations and Bland−Altman plots for days with a maximum temperature > 35 °C (PDF)

■ AUTHOR INFORMATION

Corresponding Authors

Noah Scovronick − *Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, Georgia 30322, United States;* orcid.org/0000-0003-1410-3337; Email: scovronick@emory.edu

Ajay Pillarisetti − *Division of Environmental Health Sciences, University of California Berkeley, Berkeley, California 94720, United States*; Email: ajaypillarisetti@berkeley.edu

Authors

Aniruddha Deshpande − *Department of Epidemiology, Rollins School of Public Health, Emory University, Atlanta, Georgia 30322, United States*

Thomas F. Clasen − *Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, Georgia 30322, United States*

Lance Waller − *Department of Biostatistics and Bioinformatics, Rollins School of Public Health, Emory University, Atlanta, Georgia 30322, United States*

Jiantong Wang − *Department of Biostatistics and Bioinformatics, Rollins School of Public Health, Emory University, Atlanta, Georgia 30322, United States*

Vigneswari Aravindalochanan − *Sri Ramachandra Institute of Higher Education and Research, Chennai 600116, India*

Kalpana Balakrishnan − *Sri Ramachandra Institute of Higher Education and Research, Chennai 600116, India*

Naveen Puttaswamy − *Sri Ramachandra Institute of Higher Education and Research, Chennai 600116, India*; orcid.org/0000-0002-8221-1682

Jennifer Peel − *Department of Epidemiology, Colorado State University, Aurora, Colorado 80523, United States*

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.3c03461

Notes

The authors declare no competing financial interest.

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