Science of the Total Environment 707 (2020) 136114

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Identifying predictors of personal exposure to air temperature in peri-urban India

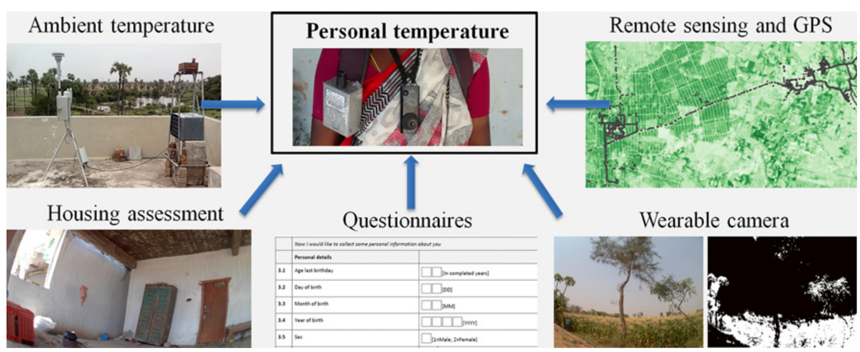
Carles Milà [a], Ariadna Curto [a], Asya Dimitrova [a], V. Sreekanth [b,c], Sanjay Kinra [d], Julian D. Marshall [b], Cathryn Tonne [a,*]

[a] ISGlobal, Universitat Pompeu Fabra, CIBER Epidemiología y Salud Pública, Barcelona, Spain
[b] Department of Civil and Environmental Engineering, University of Washington, Seattle, WA, USA
[c] Center for Study of Science, Technology & Policy, Bengaluru 560 094, India
[d] Department of Non-communicable Disease Epidemiology, London School of Hygiene and Tropical Medicine, London, UK

HIGHLIGHTS

- Limited agreement between ambient and personal air temperature
- Overall moderate correlation between ambient and personal air temperature
- Nighttime predictors included household altitude, ceiling height, and income.
- Daytime predictors included housing characteristics and GPS-tracked altitude.
- Time in agricultural labour was predictive in women and time travelling in men.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 15 July 2019
Received in revised form 12 December 2019
Accepted 12 December 2019
Available online 13 December 2019

Editor: Scott Sheridan

Keywords:
Heat
GPS
Remote sensing
Wearable camera
Greenspace
Urban heat island

ABSTRACT

Characterizing personal exposure to air temperature is critical to understanding exposure measurement error in epidemiologic studies using fixed-site exposure data and to identify strategies to protect public health. To date, no study evaluating personal air temperature in the general population has been conducted in a low-and-middle income country.

We used data from the CHAI study consisting of 50 adults monitored in up to six non-consecutive 24 h sessions in peri-urban south India. We quantified the agreement and association between fixed-site ambient and personal air temperature, and identified predictors of personal air temperature based on housing assessment, self-reported, GPS, remote sensing, and wearable camera data.

Mean (SD) daytime (6 am–10 pm) average personal air temperature was 31.2 (2.6) °C and mean nighttime (10 pm–6 am) average temperature was 28.8 (2.8) °C. Agreement between average personal air and fixed-site ambient temperatures was limited, especially at night when personal air temperatures were underestimated by fixed-site temperatures (MBE = −5.6 °C). The proportion of average personal nighttime temperature variability explained by ambient fixed-site temperatures was moderate (R^2_{mar} = 0.39); daytime associations were stronger for women (R^2_{mar} = 0.51) than for men (R^2_{mar} = 0.3). Other predictors of average nighttime personal

Abbreviations: LMIC, low-and-middle income country; GPS, Global Positioning System; CHAI, Cardiovascular Health effects of Air pollution in Telangana, India; APCAPS, Andhra Pradesh Children and Parents Study; ICC, intraclass correlation coefficient; RMSE, root mean square error; UHI, urban heat island; GVI, Green View Index; NDVI, Normalized Difference Vegetation Index; R^2_{mar}, marginal R^2; AC, air conditioning; AM, arithmetic mean; SD, standard deviation; MBE, mean bias error; CI, confidence interval.

* Corresponding author at: ISGlobal, Universitat Pompeu Fabra, CIBER Epidemiología y Salud Pública, Doctor Aiguader 88, 08003 Barcelona, Spain.
E-mail address: cathryn.tonne@isglobal.org (C. Tonne).

https://doi.org/10.1016/j.scitotenv.2019.136114

air temperature included residential altitude, ceiling height, and household income. Predictors of average daytime personal air temperature included roof materials, GPS-tracked altitude, time working in agriculture (for women), and time travelling (for men). No biomass cooking, urban heat island, or greenspace effects were identified.

R^2_{mar} between ambient fixed-site and personal air temperature indicate that ambient fixed-site temperature is only a moderately useful proxy of personal air temperature in the context of peri-urban India. Our findings suggest that people living in houses at lower altitude, with lower ceiling height and asbestos roofing sheets might be more vulnerable to heat. We also identified households with higher income, women working in agriculture and men with long commutes as disproportionately exposed to high temperatures.

1. Introduction

There is growing evidence of the health effects of thermal stress in low-and-middle income countries (LMICs) (Green et al., 2019). Studies in India have estimated significant associations between heat and increased mortality and morbidity (Fu et al., 2018; Salve et al., 2018), as well as decreased worker productivity (Venugopal et al., 2016). Yet, recent evidence has also revealed a larger contribution of moderately cold temperatures to mortality than moderately hot and extremely hot and cold temperatures, which can be partly explained by the higher frequency of moderately cold days in parts of India (Fu et al., 2018). Modifiers of temperature-mortality associations include physiological factors such as gender, age, and pre-existing chronic diseases and morbidities; but also potentially other factors that may relate to temperature exposure such as occupation and socio-economic status (Ingole et al., 2017; Son et al., 2019).

Personal monitoring of environmental exposures is increasingly feasible with low cost devices, with possibility of improved, individual-level exposure assessment in epidemiologic studies (Tonne et al., 2017a). While in air pollution epidemiology there is an increasing use of wearable sensors to measure personal exposure to air pollutants (Steinle et al., 2013), temperature epidemiology studies have predominantly relied on ambient (i.e., measuring the background, environmental air temperature away from local sources of heat) fixed-site temperature measurements (Gasparrini et al., 2015) or gridded modelled ambient temperatures (Fu et al., 2018) as proxies of personal exposure (i.e., the contact between an individual and air temperature at exposure surfaces of the skin and lungs). Exposure measurement error in population studies when using fixed-site or gridded estimates has not been well characterized, largely due to the general lack of data on personal air temperature (Kuras et al., 2017). Identifying predictors of personal exposure can inform potential risk prevention strategies needed to protect public health (Lioy, 2010). This issue is increasingly a priority as part of climate change adaptation strategies given that heat waves are expected to be longer, more frequent, and more severe (Murari et al., 2015) due to global warming (IPCC, 2014) by the second half of the century in India.

Most studies that have measured personal air temperature exposure are based on occupationally exposed individuals (Runkle et al., 2019; Sugg et al., 2019, 2018; Uejio et al., 2018; Xiang et al., 2014) and may therefore have limited generalizability to the general population. The few studies that have performed personal monitoring of temperature in the general population have been conducted in high-income countries (Basu and Samet, 2002; Bernhard et al., 2015; Brook et al., 2011; Kuras et al., 2015). Of these, one study included residents of rural communities (Bernhard et al., 2015) and two considered factors other than ambient temperature that could affect personal exposure (e.g., household income, education, and occupation), and those factors were self-reported (Bernhard et al., 2015; Kuras et al., 2015). Although previous studies have used GPS derived location to investigate the influence of location and time-activity on personal temperature in occupationally exposed populations (Sugg et al., 2018), to our knowledge, no previous studies to date have evaluated how personal exposure to temperature is influenced by objectively-measured microenvironments derived from wearable cameras.

Here, we use a data-driven approach to identify predictors of personal air temperature in a sample of the general population in peri-urban south India. Our specific objectives were to 1) quantify the agreement and association between ambient fixed-site and personal air temperature exposure and 2) identify additional predictors of personal exposure to air temperature based on housing assessment, self-reported, GPS, remote sensing, and wearable camera data.

2. Materials and methods

2.1. Study population and monitoring sessions

We used data from the panel study of the Cardiovascular Health effects of Air pollution in Telangana, India (CHAI) project (Tonne et al., 2017b). CHAI was approved by the Ethics Committees of Parc de Salut Mar (Barcelona, Spain), the Indian Institute of Public Health-Hyderabad (Hyderabad, India), and the National Institute of Nutrition (Hyderabad, India). CHAI builds on the Andhra Pradesh Children and Parents Study (APCAPS) cohort (Kinra et al., 2014), which included 6944 participants distributed in 28 villages in a peri-urban area south of the city of Hyderabad, India (Fig. S1). CHAI added extensive ambient and personal air pollution monitoring in a random gender and village-stratified sample ($n = 401$) of the APCAPS population. A random subsample of 60 CHAI participants was also included in the panel study, whose objective was to identify locations and activities with high particulate air pollution concentrations using ambient, GPS, wearable camera, and personal air pollution monitors (Milà et al., 2018) (Fig. 1). The Köppen-Geiger climate classification (Beck et al., 2018) of the study area is tropical wet and dry, characterized by warm temperatures (coldest monthly air temperature above 18 °C) and a marked dry season.

Each panel participant was monitored in up to six 24 hour non-consecutive sessions within 6 monitoring rounds set up between May 2015 and February 2016 (1st: 2015-05-13 to 2015-06-21, $n = 63$; 2nd: 2015-06-24 to 2015-07-26, $n = 52$; 3rd: 2015-08-04 to 2015-09-09, $n = 40$; 4th: 2015-09-09 to 2015-10-13, $n = 40$; 5th: 2015-12-12 to 2016-01-04, $n = 39$; 6th: 2016-01-07 to 2016-02-20, $n = 37$). Sessions were distributed across the four seasons of the study area: summer (March–May), monsoon (June–August), post-monsoon (September–November), and winter (December–February). The start of the monitoring campaign in summer 2015 happened to coincide with a heat wave affecting Telangana and other Indian states (Liberto, 2015), during which monitoring was temporally suspended to avoid an additional burden and ensure the wellbeing of the study participants, who in many cases had outdoor occupations involving physical activity. Monitoring sessions were scheduled so as to minimize the impact on participant's daily routines; they typically started at 8 am at the participant's residence and finished 24 h thereafter at the same location. A trained technician was present at both times to install and remove the monitoring devices, give instructions to the participants, answer questions, and administer a post-monitoring questionnaire. Participants

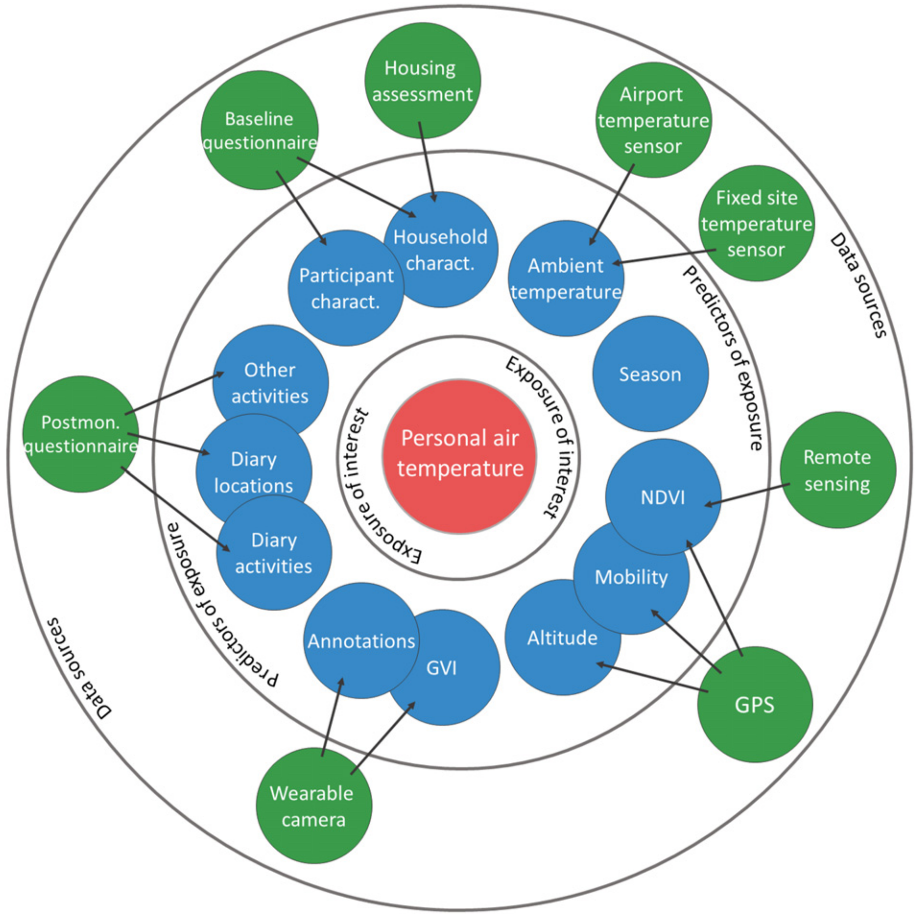


Fig. 1. Data integration graphical summary.

were instructed to place the rucksack near them when not wearing it to minimize measurement error.

2.2. Data sources

2.2.1. Personal air temperature

Continuous personal air pollution monitoring was conducted using a RTI MicroPEM v3.2A monitor (MicroPEM, RTI International, Research Triangle Park, NC 27709, USA) attached to the strap of a rucksack (Fig. S2). The device included a low-voltage, precision centigrade temperature sensor (P/N TMP-36GT9Z-ND, Analog Devices Inc., Norwood, MA, USA) that recorded ambient temperature every 30 s. The sensor was located in the sample flow stream, downstream of the filter. According to the manufacturer, the temperature range of the device was −40 °C to 100 °C; accuracy at 25 °C was ±3 °C. Upon deployment of the device, the initial temperature of the sensor was calibrated with ambient temperature (measured with HTC-1 LCD Digital Thermometer Hygrometer) using the MicroPEM Docking Station software (version 2.0). The same software was also used to download the data after monitoring. We computed 1-minute average temperature time series from the raw data (Fig. S3).

We performed a 4-hour laboratory experiment with four MicroPEM units used in the CHAI panel, a heater (Selecta Incubat), and a calibrated high-precision (±0.1 °C accuracy) thermohygrometer (Testo 635-2; used as reference) to evaluate the following for the MicroPEM temperature sensor: 1) agreement and reproducibility of measurements, 2) accuracy compared to the reference, and 3) responsiveness to temperature changes. Detailed description of the methods, materials, and results from the experiment is available in Methods S1. Briefly, we found that while agreement between MicroPEM temperature sensors was excellent (intraclass correlation coefficient, ICC = 1), their response time was slow, resulting in differences in air temperature compared to the reference (root mean square error, RMSE = 1.7–2.1 °C among the four MicroPEM units) with successive 5 °C temperature increments every 30 min.

2.2.2. Ambient air temperature

Hourly ambient temperature was recorded at a fixed-location site in the north of the study area (Digit THL, LabJack Corporation, Lakewood, CO 80227 USA) (Fig. S1). Ambient monitoring started one month later than personal monitoring (June 2015); we therefore imputed data for May 2015 using temperature data from Hyderabad south airport located 16 km away from the ambient north site (Fig. S1) following previously used methods for ambient fixed-site air pollution imputation in the CHAI project (Milà et al., 2018). Namely, we fitted a linear regression model to ambient north site temperature using airport temperature and hour categorical indicators as predictors. The model had an adjusted-R^2 of 0.94; we used this model to predict north site hourly temperature for May 2015.

2.2.3. Questionnaires and housing assessment

CHAI participants completed a baseline questionnaire containing information about time-invariant demographic (age, gender), socioeconomic (education, occupation) and household (income, assets) characteristics. Bedroom materials, dimensions, and number of windows were assessed by a trained technician. Furthermore, a post-monitoring questionnaire was administered at the end of each monitoring session. The questionnaire included a series of questions about total daily time spent in certain activities (e.g., cooking) and locations (e.g., travelling), as well as a diary of activities and locations with hourly slots.

2.2.4. GPS

Panel participants' longitude, latitude, and altitude were recorded every 30 s through a GPS device (Etrex 20; Garmin, Inc., Fig. S4) participants carried in a secured backpack. The accuracy of the GPS in the study area was 4 m; we inspected and cleaned the tracks to exclude points with abrupt changes of position (>1 km) and cold starts (>50 m from residence at the start of the session). The front door of all participants' households was geocoded by field workers. We identified points within the Hyderabad ring road (identified through aerial tracing of OpenStreetMap) to explore potential urban heat island effects (UHI). We also applied a map-matching spatiotemporal clustering algorithm (Donaire-gonzalez et al., 2016; Sanchez et al., 2017) to the GPS tracks to identify locations visited during the monitoring. Detected clusters at a linear distance smaller than 10 m from the participant's home were labelled as "home" whereas the rest of clusters were considered "places other than home". A point was considered to belong to a cluster if the distance in time and space was <10 m/30 min, respectively. The remaining points were classified as "trips".

2.2.5. Wearable camera

Panel participants carried a wearable camera (Autographer, OMG Life, Oxford, UK) that took photographs of the environment in front of the participant (180° approximately) every 35 s (Fig. S2). The battery life of the device was 10 h; participants were instructed to turn off the device at night when light conditions were poor. Participants had the option to turn off the camera when they wanted privacy and at the end of each monitoring session they could review and delete images they did not want to be part of research data. The resulting photographs were annotated by two trained technicians according to a set of locations (e.g., outdoors), activities (e.g., eating), and objects (e.g., biomass stove) set a priori. As a result, each photograph was assigned a Boolean value as having/not having a given item. The annotation protocol and validation have been described in detail elsewhere (Salmon et al., 2018). We constructed 1 min regular Boolean time series for each annotation from the photograph timestamps following previously published methods (Salmon et al., 2018).

For photographs annotated as "outdoors", we also derived a Green View Index (GVI) to identify the presence of greenspace. We used the open-source Treepedia GVI algorithm (MIT Senseable City Lab, n.d.) to detect the proportion of pixels in the photographs that corresponded to greenspace. This approach has been previously applied to Google Street View data (Li et al., 2015). Briefly, the procedure uses a normalisation of the red, green, and blue spectral image components, then employs an image segmentation algorithm to generate thematic images, and finally applies a series of rules to differentiate green vegetation features from the rest (Li et al., 2015; MIT Senseable City Lab, n.d.). An example of the GVI algorithm applied to a wearable camera photograph is shown in Fig. S5.

2.2.6. Remote sensing

We downloaded two cloudless Sentinel 2A (multi-spectral instrument) level-1C (top of atmosphere) images from the Copernicus Open Access Hub (ESA, n.d.) for the study area. The selected images corresponded to the summer (2016-04-09) and post-monsoon (2016-11-25) seasons. We used the Sen2cor v.2.5.5 processor (Louis et al., 2016) to perform atmospheric correction and obtain level-2A bottom-of-atmosphere products. We derived Normalized Difference Vegetation Index (NDVI, (NIR − red) / (NIR + red)) at 10 m spatial resolution (Fig. S6) to identify spatial patterns of greenspace in the study area. We intersected NDVI (pure intersection and 100 m buffer mean) with the GPS tracks and the geocoded households using the post-monsoon image for monitoring sessions conducted in monsoon and post-monsoon (wet seasons), and the summer image for winter and summer (dry seasons) (Fig. S6).

2.3. Data management

There were 271 24 h monitoring sessions corresponding to the 60 participants of the panel. We included 227 sessions (83%) corresponding to 50 participants in our analyses after excluding sessions with self-reported or accelerometer (in rucksack) detected non-compliance with wearing the equipment. Excluded male participants of the CHAI panel were younger than the included ones, while excluded women were less likely to work in agricultural-related occupations (Salmon et al., 2018). For nighttime analyses, 8 (3.5%) sessions were further excluded because the participant did activities other than sleeping at night, and another 12 (5.3%) were excluded because the participant reported not sleeping in the bedroom where room characteristics were recorded.

We integrated all sources of data to create three different datasets for analysis based on whether participants were sleeping and the time unit of analysis: 1) nighttime (10 pm–6 am; one observation per session, n = 207), 2) daytime (6 am–10 pm; one observation per session, n = 227), and 3) hourly daytime (6 am–10 pm; one observation per hour within session, n = 2713). More than 90% of the panel participants self-reported sleeping between 10 pm and 11 pm while a 80% still slept from 5 am to 6 am; percentages before and after this period were lower (56% sleeping between 9 pm and 10 pm, 25% sleeping between 6 am and 7 am). The three datasets contained average personal temperatures corresponding to the time ranges of the dataset and average ambient fixed-site temperatures matching personal monitoring date and time spans; time-invariant participant and household characteristics and season were also available in all datasets. The nighttime dataset included NDVI and altitude at the geocoded household, while the daytime datasets included NDVI and altitude averages computed using the corresponding GPS tracks. Daytime datasets also contained daily/hourly time spent in different locations and activities according to the GPS algorithm, the diary and other self-reported activities, and wearable camera annotations; as well as average daily/hourly GVI.

2.4. Statistical analyses

We calculated univariate descriptive statistics of all the variables included in the analysis and computed a spearman correlation matrix for continuous predictors. We calculated the Intra-class Correlation Coefficient (ICC) for personal temperatures to infer the proportion of the exposure variability happening between participants. In order to describe and plot temporal patterns in exposure, we smoothed ambient fixed-site and personal temperature time series using generalized additive models with a smooth term (cyclic cubic splines, suitable for cyclic processes (Wood, 2006)) for the time of day. We stratified daytime analyses by gender as previous results showed marked differences in mobility and time-activity patterns in this population (Sanchez et al., 2017). We investigated the agreement between average nighttime and daytime ambient fixed-site and personal temperature using Bland-Altman plots for repeated measures per participant (Bland and Altman, 2007). We evaluated the association between average nighttime and daytime ambient fixed-site and personal air temperature using linear mixed models with a random intercept per participant to account for the repeated measurements per participant. We used the marginal R^2 (R^2_{mar}), i.e., the proportion of variance explained by the fixed effects, as a measure of the strength of the association (Nakagawa and Schielzeth, 2013).

We identified predictors of nighttime, and gender-stratified daytime and hourly daytime average personal temperature exposure using the full datasets previously described. Within each dataset, we discarded predictors with little variability, i.e., if >90% of the observations had the same value (e.g., having air conditioning (AC), or time spent cooking for daytime in men). We examined missing data patterns in each dataset; the data source with the most missing entries was the wearable camera (18.1% missing in daytime dataset) followed by GPS indicators (8.8% missing in daytime dataset) (Table S1). We multiply imputed missing data using the method of the chained equations (van Buuren and Groothuis-Oudshoorn, 2011); assumptions, models, and details about the multiple imputation are given in Methods S2. In order to select the relevant exposure predictors, we used an automated stepwise procedure that was able to accommodate the repeated measures design, the multiply imputed data, and the temporal autocorrelation in hourly daytime models. A complete description of the procedure is given in Methods S3. We computed R^2_{mar} across the final models fitted in each of the imputed datasets.

Analyses were done in R v3.5.3 (R Core Team, 2019) using the following packages for data management and visualization (Grolemund and Wickham, 2011; Hijmans, 2019; Hunziker, 2017; Iannone, 2019; Pebesma, 2018; Salmon, 2017, 2016, 2013; Wickham, 2017, 2016), imputation (van Buuren and Groothuis-Oudshoorn, 2011), and modelling (Bates et al., 2015; Jaeger, 2017; Pinheiro et al., 2018; Wood, 2006). We used ArcGIS (v10.2.1), Spatialite (v4.1.1), and QGIS (v2.12.3 Lyon) to clean GPS data. GVI was computed using the Treepedia package (MIT Senseable City Lab, n.d.) in Python 3.6.4. Supplementary maps were done in QGIS (v2.18.1 Las Palmas).

3. Results

3.1. Characteristics of the study population and exposures

3.1.1. Time-invariant characteristics of the study population

Mean age of the study participants was 43.2 (standard deviation, SD 13.7) years; women were older than men and had lower literacy (Table 1). Most participants had manual occupations in the agriculture, construction, and other unskilled sectors. Only three participants reported having AC at home. The majority of participants lived in separate houses at a mean altitude of 570 m above the sea level. The most prevalent material for bedroom walls was brick whereas roof and floor materials were diverse. Houses with concrete roofs, unlike houses with asbestos roofing sheets and other materials, were all equipped with ceiling fans and had white-painted ceilings. Moreover, most houses with concrete roofs also had ventilators near the rooftop to help escape warm air.

Table 1
Study population time-invariant individual and household characteristics.

	All (n = 50)	Women (n = 25)	Men (n = 25)
Age - AM (SD)	43.2 (13.7)	47.2 (9.1)	39.2 (16.4)
Occupation - N (%)			
Manual	42 (84%)	21 (84%)	21 (84%)
Non-manual	2 (4%)	1 (4%)	1 (4%)
Unemployed	6 (12%)	3 (12%)	3 (12%)
Education - N (%)			
Illiterate	29 (58%)	20 (80%)	9 (36%)
Primary studies	8 (16%)	3 (12%)	5 (20%)
Secondary/superior studies	13 (26%)	2 (8%)	11 (44%)
Household income > 15,000 Indian rupees - N (%)	12 (24%)	6 (24%)	6 (24%)
Number of household assets - AM (SD)	4.2 (1.5)	4.4 (1.8)	4 (1.3)
Air conditioning at home - N (%)	3 (6%)	2 (8%)	1 (4%)
Household type - N (%)			
Separate house	43 (86%)	23 (92%)	20 (80%)
Shared house/apartment	7 (14%)	2 (8%)	5 (20%)
Bedroom wall material - N (%)			
Brick	43 (86%)	22 (88%)	21 (84%)
Mud/clay	7 (14%)	3 (12%)	4 (16%)
Bedroom floor material - N (%)			
Cement	11 (22%)	6 (24%)	5 (20%)
Mud/stone	22 (44%)	9 (36%)	13 (52%)
Tiles	17 (34%)	10 (40%)	7 (28%)
Bedroom roof material - N (%)			
Tiles/grass	11 (22%)	5 (20%)	6 (24%)
Asbestos sheets	15 (30%)	7 (28%)	8 (32%)
Concrete	24 (48%)	13 (52%)	11 (44%)
Bedroom size (m^2) - AM (SD)	12.8 (4.4)	12.6 (3.8)	13 (4.9)
Bedroom ceiling height (m) - AM (SD)	3 (0.3)	3.1 (0.3)	2.9 (0.3)
Bedroom number of windows - AM (SD)	0.9 (0.9)	1.1 (1)	0.8 (0.8)
Residential altitude above the sea level (m) - AM (SD)	570.2 (47.1)	575.9 (48.6)	564.5 (45.8)

3.1.2. Time-varying characteristics of the study population

Time spent in cooking-related activities was higher for women than men (e.g., mean self-reported time cooking with an indoor stove were 0.9 (SD 0.7) h for women vs. 0.1 (SD 0.3) h for men) (Fig. 2). There were gender differences in predictors related to occupation (Fig. 2): on average, while men spent more time in industry (1.7 (SD 3.4) h) than women (0 (SD 0) h), the opposite was observed for agricultural labour (1.5 (SD 2.7) h for women vs. 0.6 (SD 1.9) h for men) according to wearable camera annotations. Women spent more time at home than men (average time 13.1 (SD 3.7) h for women vs. 9 (SD 4.3) h for men) according to GPS, whereas time spent travelling was longer in men (1.4 (SD 1.7) h for men vs. 0.1 (SD 0.4) h for women) according to the self-reported diary (Fig. 2).

Spearman correlations between predictors concerning similar activities and locations measured by different data sources were all positive (Fig. S7). For instance, correlation between being outdoors in the field (diary) and working in the field (wearable camera) was 0.56. Likewise, the daytime correlation between GVI and GPS-intersected NDVI was positive, yet modest ($\rho_{spearman} = 0.26$, Fig. S8).

3.1.3. Characteristics of personal exposures and fixed-site air temperature

Mean personal air temperatures were similar to ambient fixed-site temperatures for daytime hours (31.2 (SD 2.6) °C personal vs. 30.3 (SD 3.5) °C ambient) and higher for nighttime hours (28.8 (SD 2.8) °C personal vs. 23.3 (SD 3.7) °C ambient) (Table 2). No differences in personal exposure to temperature across genders were observed (e.g., daytime mean 31.2 (SD 2.7) °C in men vs. 31.3 (SD 2.4) °C in women) (Table 2). Most of the variability in personal air temperature occurred within participant: the ICC for daytime personal air temperature was 15% for men and 9% for women; the ICC for nighttime personal air temperature was 9%.

Seasonal and daytime/nighttime contrasts were stronger in ambient fixed-site temperature than in personal (Fig. 3). The highest nighttime/daytime and personal/fixed-site temperatures were in the summer season (e.g., mean personal daytime air temperature was 33.9 °C (SD 1.9) in summer) (Table S2). Mean personal temperatures were always higher than ambient fixed-site except during daytime in the summer season, when ambient fixed-site temperatures were warmer than personal (Table S2).

3.2. Agreement and association between average ambient fixed-site and personal temperature exposure

Addressing our first objective, there was a substantial discrepancy between average ambient fixed-site and personal temperatures at night (Fig. 4), when ambient fixed-site temperatures underestimated personal air temperatures (mean bias error, MBE = −5.6 °C). Mean absolute difference during daytime was smaller (MBE = −1.0 °C for men and − 0.9 °C for women), although the estimated limits of agreement were wide and larger than ±5 °C in all cases. Bland-Altman plots suggested presence of proportional bias, e.g., underestimation of personal nighttime air temperatures was smaller for warm summer than for moderately cold winter temperatures.

The strength of the association between average ambient fixed-site and personal temperature was moderate (Fig. 5). While more than half of the personal temperature exposure variability was explained

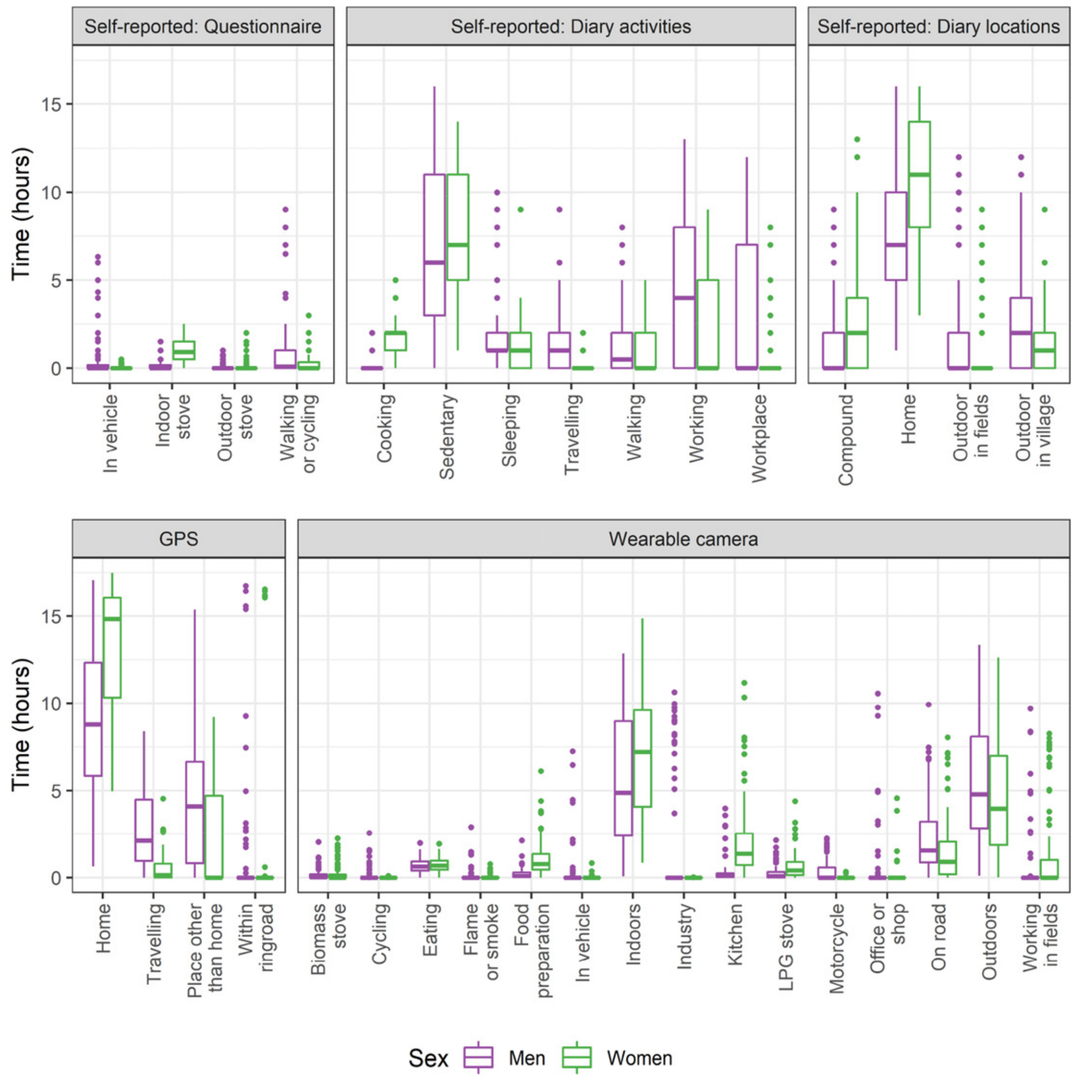


Fig. 2. Daytime time-varying activities and locations by data source and gender. The lower and upper hinges of the box correspond to the 25th and 75th percentiles, the bold bar represents the median. Whiskers defined as the highest/lowest value within 1.5 ∗ interquartile range from the hinge, values beyond that are plotted as points representing outliers.

by ambient fixed-site temperatures in women ($R^2_{mar} = 0.51$), the proportion for men was lower ($R^2_{mar} = 0.30$). Estimated slopes were similar for daytime and nighttime temperatures. No effect modification by season was found (interaction between ambient fixed-site temperature and season on personal air temperatures resulted in p-values > 0.2).

3.3. Predictors of personal exposure to air temperature

Addressing our second objective, predictors of nighttime average personal air temperature (Table 3) included ambient fixed-site temperature and the geocoded altitude of the household (−1.17 (95% confidence interval, CI −1.87, −0.46) °C for a 100 m increase). Other relevant household variables were the ceiling height of the bedroom (−1.61 (95% CI −3.08, −0.15) °C for 1-meter increase), and a household income > 15,000 Indian rupees (0.73 (0, 1.47) °C). The mean R^2_{mar} of the model in the imputed datasets was 0.48 (range 0.45 to 0.49).

Daytime personal air temperature predictors (Table 3) included ambient fixed-site temperature and asbestos roofing sheets for both genders. For women, 1 hour working in the field as measured with the wearable cameras was estimated to increase average daytime personal temperature by 0.1 (95% CI: −0.02, 0.22) °C. For men, the average altitude measured with the GPS tracks had a negative effect on average personal air temperature (−1.47 (95% CI: −2.38, −0.56) °C for a 100 meter increase). Moreover, we estimated a 0.21 (95% CI: 0.02, 0.39) °C personal temperature increase in men for each hour spent in trips according to the GPS. Mean R^2_{mar} for women's models was 0.56 (range 0.53 to 0.58) and for men's it was 0.45 (range 0.41 to 0.48).

Table 2
Summary statistics of average daytime (6 am–10 pm) and nighttime (10 pm–6 am) ambient and personal temperature exposures.

Exposures	Min	Q25	Mean	Median	Q75	Max	SD
Average personal daytime temperature (°C)	24.2	29.4	31.2	31.4	32.9	38.5	2.6
Average ambient daytime temperature (°C)	24.8	27.6	30.3	29.7	32.3	42.6	3.5
Average personal nighttime temperature (°C)	19.9	26.9	28.8	29.0	30.5	35.7	2.8
Average ambient nighttime temperature (°C)	14.9	21.0	23.3	23.6	25.4	32.5	3.7

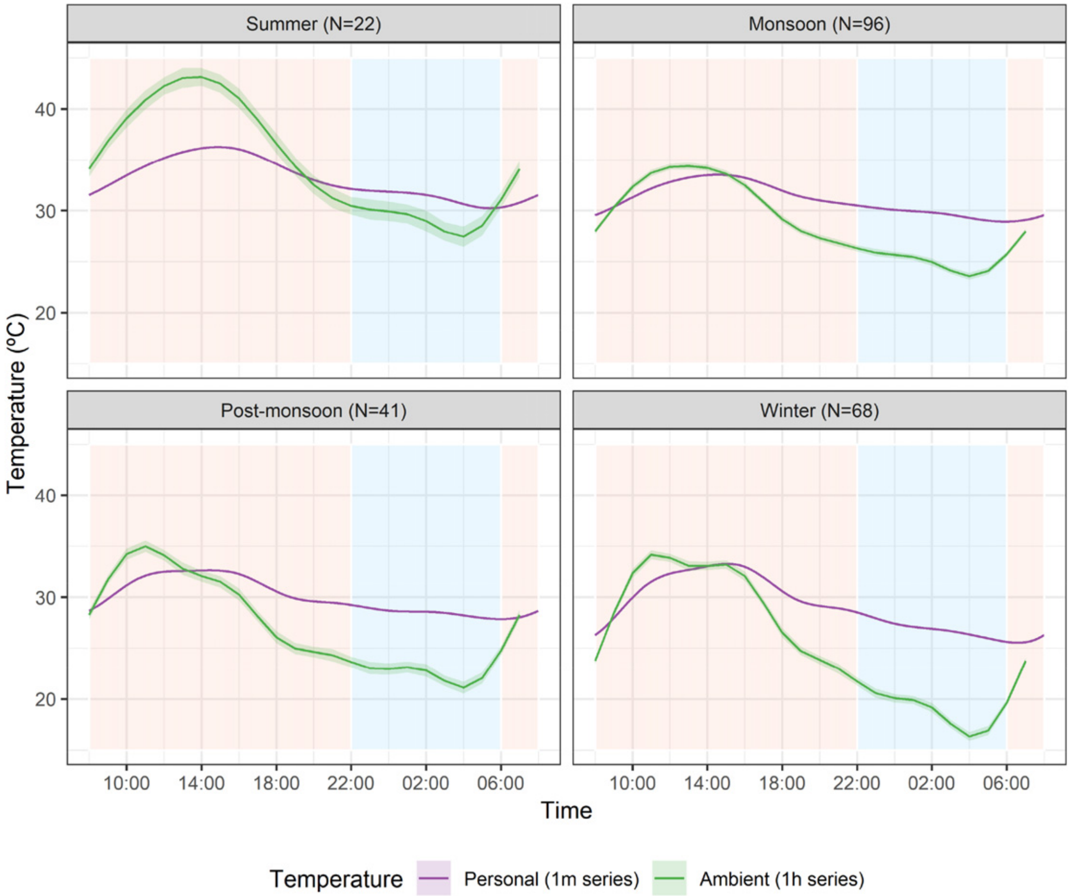


Fig. 3. Temporal patterns of personal and ambient temperature exposure by season. Orange and blue shaded areas represent daytime (6 am–10 pm) and nighttime (10 pm–6 am) as defined in this study. Estimates and 95% CI (shaded bands) were derived with generalized additive models with a smooth term for the time of day.

Similarly, gender-stratified models for hourly average daytime personal temperature identified ambient fixed-site temperature, bedroom roof material, and altitude as predictors in both men and women's models (Table S3). Time spent working according to the self-reported diary (e.g., 0.53 °C (95% CI 0.18, 0.88) per hour worked in women) and time spent outdoors according to the wearable camera (e.g., 0.82 °C (0.47, 1.17) per hour spent outdoors in women) were also predictive for both genders. Working in the field according to the wearable

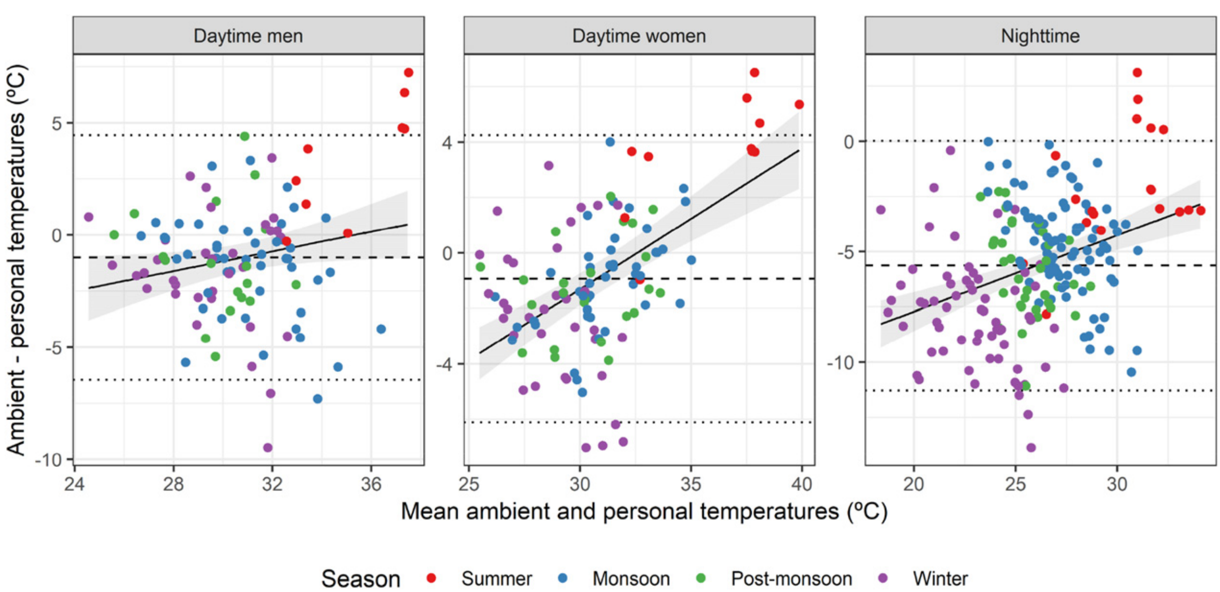


Fig. 4. Bland-Altman plots of average ambient and personal temperature exposure. The dashed line represents the mean difference between ambient and personal temperature exposures. Dotted lines representing limits of agreement calculated following Bland and Altman methods for repeated measures. The bold line represents the linear fit (mixed model with a random intercept per participant) of the mean personal and ambient temperature on the difference between ambient and personal temperature (shaded area represents its 95% CI).

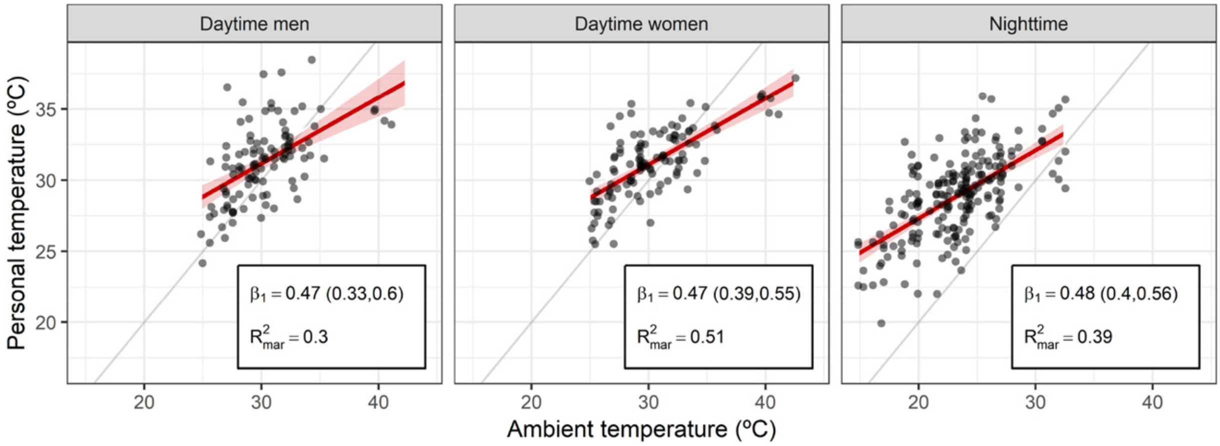


Fig. 5. Associations between average ambient and personal temperature exposure. Linear mixed models with a random intercept per participant. R^2_{mar} (or marginal R^2) corresponds to the proportion of personal temperature variance explained by fixed factors, i.e. ambient temperature.

cameras had an effect on average hourly daytime personal temperature only for women; time spent travelling was predictive only for men.

4. Discussion

We investigated the agreement and the association between ambient fixed-site and personal air temperature in a representative sample of the adult population in peri-urban India and identified self-reported and objectively-measured predictors of personal air temperature exposure. Agreement between average personal and fixed-site temperatures was limited, especially at nighttime when personal temperatures were underestimated by ambient fixed-site temperatures. The proportion of average personal nighttime temperature variability explained by ambient fixed-site temperatures was moderate; daytime associations were stronger for women than for men. In addition to ambient fixed-site temperature, we identified several household characteristics predictive of average nighttime personal temperature (e.g., residential altitude), and housing characteristics (e.g., roof material), individual activities (e.g., time spent travelling), and locations (e.g., time spent working in fields) predictive of average daytime personal temperatures. We did not identify UHI, biomass cooking, or greenspace effects.

Table 3
Predictors of average nighttime (10 pm–6 am) and gender-stratified predictors of average daytime (6 am–10 pm) of personal exposure to air temperature.

Temperature predictors	Data source	Change in °C (95% CI)
Nighttime (n = 207)		
Ambient temperature (1 °C increase)	Ambient fixed site	0.5 (0.42, 0.58)
Residential altitude (100 m increase)	GPS	−1.17 (−1.87, −0.46)
Bedroom ceiling height (1 m increase)	Baseline questionnaire	−1.61 (−3.08, −0.15)
Household income >15,000 Indian rupees (vs. below)	Baseline questionnaire	0.73 (0, 1.47)
Daytime women (n = 117)		
Ambient temperature (1 °C increase)	Ambient fixed site	0.47 (0.39, 0.55)
Asbestos sheet bedroom roof (vs. tiles/grass)	Baseline questionnaire	1.34 (0.21, 2.47)
Concrete bedroom roof (vs. tiles/grass)	Baseline questionnaire	0.14 (−0.88, 1.16)
Working in field (1 h increase)	Wearable camera	0.1 (−0.02, 0.22)
Men (n = 110)		
Ambient temperature (1 °C increase)	Ambient fixed site	0.45 (0.32, 0.58)
Asbestos sheet bedroom roof (vs. tiles/grass)	Baseline questionnaire	0.91 (−0.21, 2.04)
Concrete bedroom roof (vs. tiles/grass)	Baseline questionnaire	−0.67 (−1.73, 0.39)
Shared house/Apartment (vs. separate house)	Baseline questionnaire	1.22 (−0.01, 2.45)
Individual altitude (100 m increase)	GPS	−1.47 (−2.38, −0.56)
Travelling (1 h increase)	GPS	0.21 (0.02, 0.39)

Linear mixed models (random intercept per participant) fit to multiply imputed datasets and pooled using Rubin's rules.

4.1. Agreement and association with ambient fixed-site temperature exposure

We found that agreement between daytime average personal and ambient fixed-site temperatures was limited and depended on the season. Aligned with our results, previous studies in the US in the general population show that average ambient fixed-site temperature tended to overestimate personal air temperatures in the summer season (Bernhard et al., 2015; Kuras et al., 2015). However, evidence in outdoor workers in the US in the summer season shows slightly warmer mean personal than ambient fixed-site temperatures (Uejio et al., 2018), which were associated with longer time working outdoors. We found that average personal nighttime temperatures were warmer than ambient fixed-site, which agrees with results of a study evaluating indoor and outdoor nighttime summer temperatures in New York (Quinn et al., 2017), even when considering that most of the included households had indoor AC systems. The wide estimated limits of agreements both at daytime and nighttime indicated limited agreement between ambient fixed-site and personal exposures and possibly reflected the influence of other factors affecting personal air temperature.

We identified a higher proportion of average daytime personal temperature variability explained by ambient fixed-site temperatures in women than in men. Although we hypothesised that these differences could be due to higher mobility and a wider range of activities in men, the R^2_{mar} in women's multiple regression models were still higher than men's. Our estimated associations were broadly similar to previous evidence in the US: Bernhard and colleagues estimated a linear association between average hourly ambient fixed-site and personal temperature of 0.37 (95% CI: 0.35, 0.39) in multiple regression models (Bernhard et al., 2015) (our estimates were 0.32 (95% CI: 0.28, 0.36) for women and 0.38 (95% CI: 0.34, 0.43) for men in multiple hourly daytime regression models).

4.2. Spatial temperature exposure misalignment

Our results provide insights into potential exposure measurement error in epidemiologic studies based on fixed-site exposure assessment.

Despite the limited variability in altitude in our study area, we found decreased personal air temperatures for participants dwelling and travelling in more elevated areas. Although the negative association between altitude and temperature is well established for ambient fixed-site temperature (Parsons, 2014), to our knowledge there is no previous evidence of altitude effects in personal air temperature in the general population. Empirically, we found that the change in temperature with elevation above sea level is similar for personal air temperature as what one would expect for ambient fixed-site temperatures based on simple physics (i.e., adiabatic lapse rate). Another spatially-related predictor of personal air temperature is travel. In agreement with our results, studies in the US also found that indoor environments (compared to outdoors) resulted in decreased personal air temperature (Bernhard et al., 2015; Sugg et al., 2018). However, comparability between studies in high and LMICs may be limited due to differences in transport modes and access to in-vehicle AC.

4.3. Household and individual predictors of personal exposure to temperature

Household characteristics were predictive of mean personal air temperature during nighttime and daytime. Housing materials, and especially roof materials, have been identified as an important factor explaining indoor thermal comfort (Latha et al., 2015). Research on the thermal properties of asbestos roofing sheets has demonstrated their good insulating properties (Onyeaju et al., 2012); however, our results indicate that participants dwelling in houses with these roofs experienced higher daytime average temperatures compared to concrete or other materials. We believe that this is because unlike houses with asbestos rooftops, dwellings with concrete roofs were equipped with fans, ventilators, and had white-painted ceilings; and thus, roof type information acted as a marker of housing quality and adaptation to heat. In addition to housing materials, other features of buildings such as building orientation, ventilation and building space usage have also been shown to be important for keeping indoor environments cool (Latha et al., 2015). We found that higher household income was associated with higher mean temperature in nighttime models. These results were unexpected as previous evidence estimated lower personal air temperature exposure in participants with higher household income (Bernhard et al., 2015), and lower household income has been found to increase vulnerability to heat effects (Son et al., 2019).

We found a positive association between time spent working in agriculture and personal air temperature in daytime models for women, and with time working in any occupation and time spent outdoors in hourly daytime models for men and women. Previous occupational studies have identified outdoor workers in sectors such as agriculture and construction to be at risk of heat effects, especially in LMICs within tropical regions (Xiang et al., 2014) and specifically in India (Venugopal et al., 2016). Even though biomass indoor cooking has been recently reported to affect indoor thermal comfort in Indian rural households (Ravindra et al., 2019), we did not find any effect of cooking on personal air temperature. We hypothesise that this may be because solid fuel use for cooking was mostly conducted outdoors (75% of time) according to wearable camera annotations.

4.4. Effect of greenspace and urban heat island on personal temperature exposure

Even though urban greenspace has been found to have a cooling effect on ambient air temperature (Bowler et al., 2010) and may be an effect modifier in heat epidemiological analyses (Son et al., 2019), we did not find an association between greenspace, either measured by GPS or wearable camera, and personal air temperature. Similar results have been observed in an occupational study in the US (Sugg et al., 2018), where no correlation between land use (including developed areas, open areas, and forests) and personal air temperatures was observed. Cooling effects of greenspace have been found to be fairly localized (Bowler et al., 2010), and so they were likely undetectable for locations in which participants spent short duration of time (e.g., in transit). However, we also did not observe an association with greenspace and nighttime personal air temperature when participants were at home. A possible explanation for this is that findings based on urban areas have limited generalizability to peri-urban and rural areas where greenspace is primarily cropland (Taylor and Hochuli, 2017). Further research is needed to identify the impact of different types of greenspace on personal air temperature outside of urban areas, e.g., differentiating the impact of tree canopies vs. crops.

Although UHI effects have been identified in many cities in south Asia (Kotharkar et al., 2018), we did not find any indication of UHI as explained by time spent within Hyderabad's ring road. This might be because very few participants entered the city and mostly stayed in the peri-urban area. Furthermore, recent evidence suggests that urban daytime surface temperature in some Indian cities may actually be lower than its surrounding non-urban areas in dry pre-monsoon seasons, when vegetation is scarce and evapotranspiration is low (Shastri et al., 2017). This so-called "urban oasis effect" has also been observed in other geographical regions and has been attributed to low vegetation cover and surface moisture in the surrounding environment (Fan et al., 2017; Georgescu et al., 2011).

4.5. Prevention strategies and potential interventions

According to our findings, targets for interventions for health protection should include housing quality and building adaptation to heat to keep indoor environments a cool as possible. In the context of climate change, population growth and rising energy demand in India and other LMICs, improved building adaptation to heat can provide a more sustainable and affordable solution for thermal comfort than the expansion of energy and carbon intensive cooling devices such as ACs (Akpinar-Ferrand and Singh, 2010). The vulnerability of agricultural workers in peri-urban areas supports the need for prevention strategies at the national, regional, and local levels to protect the health of outdoor workers (Nilsson and Kjellstrom, 2010). Finally, heat early warning systems encompassing both rural and urban areas, as well as daytime and nighttime temperatures, should be prioritised and continuously adapted to the changing climate (Hess and Ebi, 2016).

4.6. Strengths and limitations

To our knowledge, this is the first study evaluating personal air temperature in a sample of the general population within a LMIC. This is also the first study including a large range of objectively-measured predictors of personal air temperature, including individual and household characteristics, mobility, activities, and greenspace. The main limitation of the study was the low accuracy of the personal temperature sensor. The manufacturer-reported accuracy of the sensor (± 3 °C) was poorer than temperature sensors available for personal monitoring such as HOBO and iButton (from ± 0.2 °C to ± 1 °C) (Kuras et al., 2017) and showed a slow response time under changes in air temperature in our laboratory experiment. However, all sensors were calibrated before deployment and showed an excellent agreement between each other. Due to the slow response time, we focused our results on average temperature and averaging times of an hour or more. Our estimated regression coefficients were smaller than the manufacturer-reported accuracy: although random error in the measurements (dependent variable in our regression models) could have inflated standard errors of regression coefficients, it is difficult to predict the effect of the sensor lag on results even after averaging. We had data on AC ownership, but not whether participants used AC during the monitoring. However, only three participants reported having AC, so we expect AC usage to have a limited effect on our results. Finally, we did not have data on other parameters relevant to personal heat exposure (personal radiation, humidity, and air velocity) (Kuras et al., 2017).

5. Conclusions

R^2_{mar} between ambient fixed-site and personal air temperature indicate that ambient fixed-site temperature is only a moderately useful proxy of personal temperature in epidemiologic studies in the context of a peri-urban area in India. Our results highlight additional factors that should be taken into account in epidemiological studies, for example altitude – either through spatially-resolved ambient fixed-site temperature that accounts for altitude, or by exploring exposure measurement error by altitude in studies based on fixed site monitoring. In addition to demographics, our results provide further evidence that several additional factors representing differential exposure measurement error should be explored in epidemiological studies based on fixed site monitors including: 1) housing materials and dimensions 2) occupation 3) socio-economic factors 4) mobility and 5) time spent indoors/outdoors.

CRediT authorship contribution statement

Carles Milà: Conceptualization, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Ariadna Curto:** Conceptualization, Validation, Investigation, Writing - review & editing. **Asya Dimitrova:** Resources, Writing - review & editing. **V. Sreekanth:** Resources, Investigation, Writing - review & editing. **Sanjay Kinra:** Resources, Writing - review & editing. **Julian D. Marshall:** Resources, Writing - review & editing. **Cathryn Tonne:** Conceptualization, Resources, Writing - review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank all CHAI participants as well as the field team who collected the information used in this study. We acknowledge the EU Copernicus Programme (Sentinel 2 mission) for the remote sensing data and the openstreetmap community for the study area geometries we used. We would also like to thank Mar Viana from IDAEA-CSIC for providing microPEM filters, Lidia Cañas and Sílvia Borràs for the laboratory equipment needed for temperature experiments, and the Research Quality Service from University of Barcelona (UB) from which we rented the Testo thermohygrometer.

Funding

This research was funded by the European Research Council under ERC Grant Agreement number 336167 for the CHAI Project. Cathryn Tonne was funded through a Ramón y Cajal fellowship (RYC-2015-17402) awarded by the Spanish Ministry of Economy and Competitiveness. None of the funding sources had a role in study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.136114.

References

Akpinar-Ferrand, E., Singh, A., 2010. Modeling increased demand of energy for air conditioners and consequent CO2 emissions to minimize health risks due to climate change in India. Environ. Sci. Pol. 13, 702–712. https://doi.org/10.1016/j.envsci.2010.09.009.

Basu, R., Samet, J.M., 2002. An exposure assessment study of ambient heat exposure in an elderly population in Baltimore, Maryland. Environ. Health Perspect. 110, 1219–1224. https://doi.org/10.1289/ehp.021101219.

Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using {lme4}. J. Stat. Softw. 67, 1–48. https://doi.org/10.18637/jss.v067.i01.

Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., Wood, E.F., 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. Sci. Data 5, 180214.

Bernhard, M.C., Kent, S.T., Sloan, M.E., Evans, M.B., McClure, L.A., Gohlke, J.M., 2015. Measuring personal heat exposure in an urban and rural environment. Environ. Res. 137, 410–418. https://doi.org/10.1016/j.envres.2014.11.002.

Bland, J.M., Altman, D.G., 2007. Agreement between methods of measurement with multiple observations per individual. J. Biopharm. Stat. 17, 571–582. https://doi.org/10.1080/10543400701329422.

Bowler, D.E., Buyung-Ali, L., Knight, T.M., Pullin, A.S., 2010. Urban greening to cool towns and cities: a systematic review of the empirical evidence. Landsc. Urban Plan. 97, 147–155. https://doi.org/10.1016/j.landurbplan.2010.05.006.

Brook, R.D., Shin, H.H., Bard, R.L., Burnett, R.T., Vette, A., Croghan, C., Williams, R., 2011. Can personal exposures to higher nighttime and early-morning temperatures increase blood pressure? J. Clin. Hypertens. (Greenwich) 13, 881–888. https://doi.org/10.1111/j.1751-7176.2011.00545.x.

Donaire-gonzalez, D., Valentín, A., Nazelle, A. De, Ambros, A., 2016. Benefits of mobile phone technology for personal environmental monitoring. JMIR Mhealth Uhealth 4. https://doi.org/10.2196/mhealth.5771.

ESA, n.d.. Copernicus Open Access Hub (WWW Document, accessed 1.10.19).

Fan, C., Myint, S.W., Kaplan, S., Middel, A., Zheng, B., Rahman, A., Huang, H.-P, Brazel, A., Blumberg, D.G., 2017. Understanding the impact of urbanization on surface urban heat islands—a longitudinal analysis of the oasis effect in subtropical desert cities. Remote Sens. 9 (7), 672. https://doi.org/10.3390/rs9070672.

Fu, S.H., Gasparrini, A., Rodriguez, P.S., Jha, P., 2018. Mortality attributable to hot and cold ambient temperatures in India: a nationally representative case-crossover study. PLoS Med. 15, 1–17. https://doi.org/10.1371/journal.pmed.1002619.

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., Tobias, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M.L., Guo, Y.-L.L., Wu, C., Kan, H., Yi, S.-M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P.H.N., Honda, Y., Kim, H., Armstrong, B., 2015. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. Lancet 386, 369–375. https://doi.org/10.1016/S0140-6736(14)62114-0.

Georgescu, M., Moustaoui, M., Mahalov, A., Dudhia, J., 2011. An alternative explanation of the semiarid urban area "oasis effect". J. Geophys. Res. Atmos. 116 (D24).

Green, H., Bailey, J., Schwarz, L., Vanos, J., Ebi, K., Benmarhnia, T., 2019. Impact of heat on mortality and morbidity in low and middle income countries: a review of the epidemiological evidence and considerations for future research. Environ. Res. 171, 80–91. https://doi.org/10.1016/j.envres.2019.01.010.

Grolemund, G., Wickham, H., 2011. Dates and times made easy with {lubridate}. J. Stat. Softw. 40, 1–25.

Hess, J.J., Ebi, K.L., 2016. Iterative management of heat early warning systems in a changing climate. Ann. N. Y. Acad. Sci. 1382, 21–30. https://doi.org/10.1111/nyas.13258.

Hijmans, R.J., 2019. raster: Geographic Data Analysis and Modeling.

Hunziker, P., 2017. velox: Fast Raster Manipulation and Extraction.

Iannone, R., 2019. Diagramme R: Graph/Network Visualization.

Ingole, V., Kovats, S., Schumann, B., Hajat, S., Rocklöv, J., Juvekar, S., Armstrong, B., 2017. Socioenvironmental factors associated with heat and cold-related mortality in Vadu HDSS, western India: a population-based case-crossover study. Int. J. Biometeorol. 61, 1797–1804. https://doi.org/10.1007/s00484-017-1363-8.

IPCC, 2014. The IPCC's Fifth Assessment Report: What's In It for South Asia (Geneva, Switzerland).

Jaeger, B., 2017. r2glmm: Computes R Squared for Mixed (Multilevel) Models.

Kinra, S., Radha Krishna, K.V., Kuper, H., Rameshwar Sarma, K.V., Prabhakaran, P., Gupta, V., Walia, G.K., Bhogadi, S., Kulkarni, B., Kumar, A., Aggarwal, A., Gupta, R., Prabhakaran, D., Reddy, K.S., Davey Smith, G., Ben-Shlomo, Y., Ebrahim, S., 2014. Cohort profile: Andhra Pradesh Children and Parents Study (APCAPS). Int. J. Epidemiol. 43, 1417–1424. https://doi.org/10.1093/ije/dyt128.

Kotharkar, R., Ramesh, A., Bagade, A., 2018. Urban Heat Island studies in South Asia: a critical review. Urban Clim. 24, 1011–1026. https://doi.org/10.1016/j.uclim.2017.12.006.

Kuras, E.R., Hondula, D.M., Brown-Saracino, J., 2015. Heterogeneity in individually experienced temperatures (IETs) within an urban neighborhood: insights from a new approach to measuring heat exposure. Int. J. Biometeorol. 59, 1363–1372. https://doi.org/10.1007/s00484-014-0946-x.

Kuras, E.R., Richardson, M.B., Calkins, M.M., Ebi, K.L., Hess, J.J., Kintziger, K.W., Jagger, M.A., Middel, A., Scott, A.A., Spector, J.T., Uejio, C.K., Vanos, J.K., Zaitchik, B.F., Gohlke, J.M., Hondula, D.M., 2017. Opportunities and challenges for personal heat exposure research. Environ. Health Perspect. 125, 85001. https://doi.org/10.1289/EHP556.

Latha, P.K., Darshana, Y., Venugopal, V., 2015. Role of building material in thermal comfort in tropical climates – a review. J. Build. Eng. 3, 104–113. https://doi.org/10.1016/j.jobe.2015.06.003.

Li, X., Zhang, C., Li, W., Kuzovkina, Y.A., Weiner, D., 2015. Who lives in greener neighborhoods? The distribution of street greenery and its association with residents' socioeconomic conditions in Hartford, Connecticut, USA. Urban For. Urban Green. 14, 751–759. https://doi.org/10.1016/j.ufug.2015.07.006.

Liberto, T. Di, 2015. India heat wave kills thousands. [WWW Document]. URL. https://www.climate.gov/news-features/event-tracker/india-heat-wave-kills-thousands, Accessed date: 22 May 2019.
Lioy, P.J., 2010. Exposure science: a view of the past and milestones for the future. Environ. Health Perspect. 118, 1081–1090. https://doi.org/10.1289/ehp.0901634.
Louis, J., Debaecker, V., Pflug, B., Main-Knorn, M., Bieniarz, J., Mueller-Wilm, U., Cadau, E., Gascon, F., 2016. Sentinel-2 SEN2COR: L2A processor for users. Proceedings of the Living Planet Symposium, Prague, Czech Republic, pp. 9–13.
Milà, C., Salmon, M., Sanchez, M., Ambrós, A., Bhogadi, S., Sreekanth, V., Nieuwenhuijsen, M., Kinra, S., Marshall, J.D., Tonne, C., 2018. When, where, and what? Characterizing personal PM2.5 exposure in periurban India by integrating GPS, wearable camera, and ambient and personal monitoring data. Environ. Sci. Technol. 52, 13481–13490. https://doi.org/10.1021/acs.est.8b03075.
MIT Senseable City Lab, d. Treepedia package for public use. [WWW Document]. URL. https://github.com/mittrees/Treepedia_Public, Accessed date: 1 August 2019 (n.d.).
Murari, K.K., Ghosh, S., Patwardhan, A., Daly, E., Salvi, K., 2015. Intensification of future severe heat waves in India and their effect on heat stress and mortality. Reg. Environ. Chang. 15, 569–579. https://doi.org/10.1007/s10113-014-0660-6.
Nakagawa, S., Schielzeth, H., 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. Methods Ecol. Evol. 4, 133–142.
Nilsson, M., Kjellstrom, T., 2010. Climate change impacts on working people: how to develop prevention policies. Glob. Health Action 3. https://doi.org/10.3402/gha.v3i0.5774.
Onyeaju, M.C., Osarolube, E., Chukwuocha, E.O., Ekuma, C.E., Omasheye, G.A.J., 2012. Comparison of the thermal properties of asbestos and polyvinylchloride (PVC) ceiling sheets. Mater. Sci. Appl. 3, 240–244.
Parsons, K., 2014. Human Thermal Environments: The Effects of Hot, Moderate, and Cold Environments on Human Health, Comfort, and Performance. CRC press.
Pebesma, E., 2018. sf: Simple Features for R.
Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., R Core Team, 2018. {nlme}: Linear and Nonlinear Mixed Effects Models.
Quinn, A., Kinney, P., Shaman, J., 2017. Predictors of summertime heat index levels in New York City apartments. Indoor Air 27, 840–851. https://doi.org/10.1111/ina.12367.
R Core Team, 2019. R: A Language and Environment for Statistical Computing.
Ravindra, K., Agarwal, N., Kaur-Sidhu, M., Mor, S., 2019. Appraisal of thermal comfort in rural household kitchens of Punjab, India and adaptation strategies for better health. Environ. Int. 124, 431–440. https://doi.org/10.1016/j.envint.2018.12.059.
Runkle, J.D., Cui, C., Fuhrmann, C., Stevens, S., Del Pinal, J., Sugg, M.M., 2019. Evaluation of wearable sensors for physiologic monitoring of individually experienced temperatures in outdoor workers in southeastern U.S. Environ. Int. 129, 229–238. https://doi.org/10.1016/j.envint.2019.05.026.
Salmon, M., 2013. watchme: R Package that Supports the Analysis of Images Annotations (WWW Document).
Salmon, M., 2016. riem: Accesses Weather Data From the Iowa Environment Mesonet.
Salmon, M., 2017. rtimicropem: CHAI data cleaning. [WWW Document]. URL. https://ropensci.github.io/rtimicropem/articles/chai_data_cleaning.html.
Salmon, M., Milà, C., Bhogadi, S., Addanki, S., Madhira, P., Muddepaka, N., Mora, A., Sanchez, M., Kinra, S., Sreekanth, V., Doherty, A., Marshall, J.D., Tonne, C., 2018. Wearable camera-derived microenvironments in relation to personal exposure to PM2.5. Environ. Int. 117, 300–307.
Salve, H..R., Parthasarathy, R., Krishnan, A., Pattanaik, D.R., 2018. Impact of ambient air temperature on human health in India. Rev. Environ. Health https://doi.org/10.1515/reveh-2018-0024.
Sanchez, M., Ambros, A., Salmon, M., Bhogadi, S., Wilson, R.T., Kinra, S., Marshall, J.D., Tonne, C., 2017. Predictors of daily mobility of adults in peri-urban South India. Int. J. Environ. Res. Public Health 14, 783.
Shastri, H., Barik, B., Ghosh, S., Venkataraman, C., Sadavarte, P., 2017. Flip flop of day-night and summer-winter surface urban heat island intensity in India. Sci. Rep. 7, 40178.
Son, J., Liu, J.C., Bell, M.L., 2019. Temperature-related mortality: a systematic review and investigation of effect modifiers. Environ. Res. Lett. 14 (7), 3004 https://iopscience.iop.org/article/10.1088/1748-9326/ab1cdb.
Steinle, S., Reis, S., Sabel, C.E., 2013. Quantifying human exposure to air pollution—moving from static monitoring to spatio-temporally resolved personal exposure assessment. Sci. Total Environ. 443, 184–193.
Sugg, M.M., Fuhrmann, C.M., Runkle, J.D., 2018. Temporal and spatial variation in personal ambient temperatures for outdoor working populations in the southeastern USA. Int. J. Biometeorol. 62, 1521–1534. https://doi.org/10.1007/s00484-018-1553-z.
Sugg, M.M., Stevens, S., Runkle, J.D., 2019. Estimating personal ambient temperature in moderately cold environments for occupationally exposed populations. Environ. Res. 173, 497–507. https://doi.org/10.1016/j.envres.2019.03.066.
Taylor, L., Hochuli, D.F., 2017. Defining greenspace: multiple uses across multiple disciplines. Landsc. Urban Plan. 158, 25–38. https://doi.org/10.1016/j.landurbplan.2016.09.024.
Tonne, C., Basagaña, X., Chaix, B., Huynen, M., Hystad, P., Nawrot, T.S., Slama, R., Vermeulen, R., Weuve, J., Nieuwenhuijsen, M., 2017a. New frontiers for environmental epidemiology in a changing world. Environ. Int. 104, 155–162. https://doi.org/10.1016/j.envint.2017.04.003.
Tonne, C., Salmon, M., Sanchez, M., Sreekanth, V., Bhogadi, S., Sambandam, S., Balakrishnan, K., Kinra, S., Marshall, J.D., 2017b. Integrated assessment of exposure to PM2.5 in South India and its relation with cardiovascular risk: design of the CHAI observational cohort study. Int. J. Hyg. Environ. Health 220, 1081–1088.
Uejio, C.K., Morano, L.H., Jung, J., Kintziger, K., Jagger, M., Chalmers, J., Holmes, T., 2018. Occupational heat exposure among municipal workers. Int. Arch. Occup. Environ. Health 91, 705–715. https://doi.org/10.1007/s00420-018-1318-3.
van Buuren, S., Groothuis-Oudshoorn, K., 2011. mice: multivariate imputation by chained equations in R. J. Stat. Softw. 45, 1–67.
Venugopal, V., Chinnadurai, S.J., Lucas, A.R., Kjellstrom, T., 2016. Occupational heat stress profiles in selected workplaces in India. Int. J. Environ. Res. Public Heal. https://doi.org/10.3390/ijerph13010089.
Wickham, H., 2016. ggplot 2: Elegant Graphics for Data Analysis. Springer-Verlag, New York.
Wickham, H., 2017. tidyverse: Easily Install and Load “Tidyverse” Packages.
Wood, S., 2006. Generalized Additive Models: An Introduction With R. CRC press.
Xiang, J., Bi, P., Pisaniello, D., Hansen, A., 2014. Health impacts of workplace heat exposure: an epidemiological review. Ind. Health 52, 91–101. https://doi.org/10.2486/indhealth.2012-0145.