



PanoMRT: Panoramic infrared thermography to model human thermal exposure and comfort

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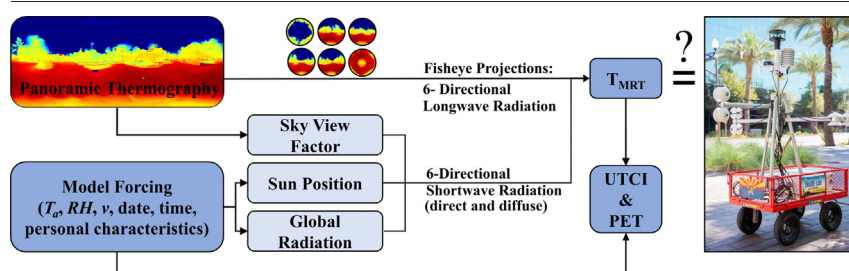
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HIGHLIGHTS

- PanoMRT calculates outdoor thermal exposure and comfort from panoramic infrared thermography.
- Surface temperatures in cities vary widely due to heterogeneous materials and shade patterns.
- 3D surface temperature information significantly improves mean radiant temperature models.

GRAPHICAL ABSTRACT



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ABSTRACT

As summer heat waves become the new normal worldwide, modeling human thermal exposure and comfort to assess and mitigate urban overheating is crucial to uphold livability in cities. We introduce *PanoMRT*, an open source human-biometeorological model to calculate Mean Radiant Temperature (T_{MRT}), Physiologically Equivalent Temperature (PET), and the Universal Thermal Climate Index ($UTCI$) from thermal equirectangular 360° panoramas and standard weather information (air temperature, relative humidity, wind speed). We validated the model for hot, dry, clear summer days in Tempe, Arizona, USA with in-situ observations using a FLIR Duo Pro R thermal camera on a rotating arm and the mobile human-biometeorological instrument platform MaRty. We observed and modeled T_{MRT} and thermal comfort for 19 sites with varying ground cover (grass, concrete, asphalt), sky view factor, exposure (sun, shade), and shade type (engineered, natural) six times per day. *PanoMRT* performed well with a Root Mean Square Error (RMSE) of 4.1 °C for T_{MRT} , 2.6 °C for PET , and 1.2 °C for $UTCI$, meeting the accuracy requirement of ± 5 °C set in the ISO 7726 standard for heat and cold stress studies. *RayMan* reference model runs without measured surface temperature forcing reveal that accurate longwave radiative flux estimations are crucial to meet the ± 5 °C threshold, particularly for shaded locations and during midday when surface temperatures peak and longwave modeling errors are largest. This study demonstrates the importance of spatially resolved 3D surface temperature data for thermal exposure and comfort modeling to capture complex longwave radiation exposure patterns resulting from heterogeneity in built configuration and material radiative and thermal properties in the built environment.

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Abbreviations

A	atmospheric radiation [Wm^{-2}]
D	diffuse shortwave radiation [Wm^{-2}]
D_{iso}	isotropic diffuse shortwave radiation [Wm^{-2}]
D_{aniso}	anisotropic diffuse shortwave radiation [Wm^{-2}]
f_{SVF}	sky view factor [–]
F_i	angular weighting factor for standing reference person for radiation incident from direction i (0.22 for N, E, S, W; 0.06 for up/down) [–]
G_0	global shortwave radiation, $f_{\text{SVF}} = 1$, cloudless [Wm^{-2}]
i	index that denotes directions (N, E, S, W, up, down)
I	direct shortwave radiation on a horizontal surface [Wm^{-2}]
I'	direct shortwave radiation on a surface perpendicular to the Sun [Wm^{-2}]
$\bar{I}_0$	solar constant (1367) [Wm^{-2}]
I_0	extraterrestrial radiation [Wm^{-2}]
K_i	directional shortwave radiation (i denotes N, E, S, W, up, down) [Wm^{-2}]
$K_1, K_2, K_{\rightarrow}$	directional shortwave radiation (arrow indicates direction) [Wm^{-2}]
L_i	directional longwave radiation (i denotes N, E, S, W, up, down) [Wm^{-2}]
L_{sky}	longwave radiation for sky pixels in thermal panorama [Wm^{-2}]
L_{pixel}	longwave radiation for non-sky pixels in thermal panorama [Wm^{-2}]
m_{RO}	relative optical air mass
N	degree of cloudiness [octas]
PET	physiologically equivalent temperature [$^{\circ}\text{C}$]
R	mean radiant flux density [Wm^{-2}]
RH	relative humidity [%]
T_a	air temperature [$^{\circ}\text{C}$]
T_L	Linke turbidity factor (4.2) [–]
T_{ped}	pedestrian surface temperature at street level [$^{\circ}\text{C}$]
T_s	surface temperature [$^{\circ}\text{C}$]
T_{MRT}	mean radiant temperature [$^{\circ}\text{C}$]
$UTCI$	Universal Thermal Climate Index
v	wind velocity [ms^{-1}]
V_p	vapor pressure [hPa]
z	altitude [m]
α	albedo (0.15) [–]
δ_{RO}	optical thickness
ε	standard emissivity (0.95) [–]
ε_p	emissivity of the human body (0.97) [–]
η	Sun's altitude (elevation) angle above the horizon [$^{\circ}$]
ϕ	solar zenith angle [$^{\circ}$]
θ	azimuth angle [$^{\circ}$]
ξ_k	absorption coefficient for shortwave radiation (0.7) [–]
ρ	local atmospheric pressure [hPa]
ρ_0	atmospheric pressure at sea level (1013) [hPa]
σ	Stefan-Boltzman constant ($5.670367 \cdot 10^{-8}$) [$\text{Wm}^{-2} \text{K}^{-4}$]
τ	transmittance of direct solar radiation [–]

1. Introduction

Land use and land cover change from urbanization coupled with climate change leads to urban overheating, i.e. thermal conditions in cities that are hazardous to people and associated urban systems (Nazarian et al., 2022). Heat has myriad negative impacts on human health (Gasparrini et al., 2015; Luber and McGeehin, 2008), comfort (Kuras et al., 2017; Middel et al., 2016), productivity (Dunne et al., 2013; Kjellstrom and Crowe, 2011), and performance (Alhadad et al., 2019; Kosaka et al., 2018). It also increases cooling energy use (Li et al., 2012), water use for irrigation (Jenerette et al., 2011), stresses urban infrastructure (Clark et al., 2019),

and negatively impacts the economy (Xia et al., 2018; Zander et al., 2015). Hotter weather is expected in the future (Russo et al., 2014), with more frequent and intense heat waves that may jeopardize the livability and sustainability of cities. Keeping people cool through targeted heat mitigation interventions is a priority of the 21st century (Broadbent et al., 2022; Jay et al., 2021).

While heat can be quantified using various temperature metrics, one of the most relevant metrics to assess human thermal exposure is the Mean Radiant Temperature (T_{MRT}), as it provides an important summary assessment of the radiation exchange between the human body and the built environment (ISO, 1998; Johansson et al., 2014; Kántor and Unger, 2011; Middel et al., 2016). T_{MRT} is a synthetic parameter that quantifies the heat load on the human body through weighted omnidirectional shortwave and longwave radiation flux densities. Under hot, dry, clear-sky weather conditions, T_{MRT} is the main meteorological factor that drives spatial variation of human thermal comfort (Lin et al., 2010) and an important parameter in many thermal comfort indices that incorporate radiative exposure, such as the Physiological Equivalent Temperature (PET) (Höppe, 1999) and Universal Thermal Comfort Index ($UTCI$) (Blazejczyk et al., 2012; Fiala et al., 2012; Jendritzky et al., 2012).

T_{MRT} varies significantly in the built environment with reported differences of over 35°C in the afternoon shade and sun (Middel et al., 2021). While spatial and temporal variation of T_{MRT} is mostly driven by shortwave radiation, lateral longwave radiation is the largest contributor to T_{MRT} in warm climates (Middel and Krayenhoff, 2019). Lindberg et al. (2014) showed that longwave fluxes become increasingly important in dense built environments with increased radiant fluxes from walls, highlighting the importance of vertical surface temperatures (T_s) for human thermal exposure. Stewart et al. (2021) introduced the concept of pedestrian surface temperature (T_{ped}), which is the weighted average of all surfaces surrounding a street-level pedestrian and is more relevant to human thermal exposure than horizontal T_s observed from above using satellite thermal imagery.

The built environment is a complex patchwork of differently oriented surface types with varying diurnal sun-exposure and radiative, thermal, roughness, and moisture characteristics, which leads to significant variations of T_s patches that contribute to T_{ped} in the urban canopy layer. Accurate T_s estimates are important for thermal exposure assessments, but spatially explicit T_s have not traditionally been observed in urban climate studies and are difficult to model without detailed 3-dimensional information on the composition and configuration of those T_s patches.

The emerging field of Urban Climate Informatics (Middel et al., 2022) offers novel sensing techniques and embraces more integrated and human-centric methods, including approaches to sense spatially resolved T_s in the urban canopy layer. For example, Aviv et al. (2021) used a rotating non-contacting infrared T_s sensor and LiDAR to create 3-dimensional T_s point clouds. Merchant et al. (2022) developed a camera system that records 360° shortwave and longwave panoramic images to fully resolve the spatial variation in shortwave and longwave radiant heat transfer in the outdoor environment.

We present an instrument setup to measure an approximation of T_{ped} in the form of thermal equirectangular 360° panoramas and introduce *PanoMRT*, an open source human thermal exposure and comfort model that calculates T_{MRT} , PET , and UTC from standard meteorological information and detailed T_s observations. Model results are validated using the mobile 6-directional instrument setup *MaRTy* (Middel and Krayenhoff, 2019) and compared to RayMan T_{MRT} calculations without T_s forcing to demonstrate the importance of spatially explicit, human-centric T_s data for human thermal exposure and comfort modeling.

2. Methods

PanoMRT is a Python-based software that calculates T_{MRT} from observed longwave radiation fluxes and modeled shortwave radiation fluxes simulating a 6-directional net radiometer setup for integral radiation measurements. To model T_{MRT} for a given location, time, and day, *PanoMRT*

requires a 360° equirectangular thermal panorama of the location and standard weather information (Fig. 1). The thermal panorama is projected into six fisheye images to calculate integral longwave radiation fluxes from pixel surface temperatures T_s and determine the sky view factor (f_{SVF}) of the location. The sun position (i.e., solar azimuth θ and zenith ϕ) is calculated from the latitude, date, and time of panorama acquisition. Standard weather data (air temperature T_a , relative humidity RH , and wind speed v) can be input from in-situ observations or automatically retrieved from the closest airport via the OpenWeather Application Programming Interface (API). 6-directional contributions of direct and diffuse shortwave radiation are then estimated from atmospheric conditions. Additional input parameters capturing characteristics of the pedestrian are used to calculate the thermal indices PET and $UTCI$.

2.1. Mean radiant temperature modeling

T_{MRT} is defined as the “uniform temperature of an imaginary enclosure in which the radiant heat transfer from the human body equals the radiant heat transfer in the actual non-uniform enclosure” (ISO, 1998). It is calculated from the mean radiant flux density R using the Stefan-Boltzmann law:

$$T_{MRT} = \sqrt[4]{R/\epsilon_p \sigma - 273.15} \text{ [}^\circ\text{C]} \quad (1)$$

R summarizes the long- (L_i) and shortwave (K_i) radiation fluxes the human body is exposed to from six directions (i) (VDI, 1994) and can be observed using a 6-directional setup or integral radiation measurements (Höppe, 1992):

$$R = \xi_k \sum_{i=1}^6 K_i F_i + \epsilon_p \sum_{i=1}^6 L_i F_i \quad (2)$$

F_i are angular weighting factors for a standing person and set to 0.22 for lateral radiation fluxes and 0.06 for upwards and downwards directed fluxes to approximate the elongated body shape (Fanger, 1972). ξ_k is an absorption coefficient for shortwave radiation (0.7), and ϵ_p is the emissivity of the human body (0.97) (VDI, 1994).

While *PanoMRT* estimates the longwave components of R from observed, pixel-based T_s in thermal panoramas, it uses a hybrid radiation flux density modeling approach that draws from existing T_{MRT} models to calculate diffuse and global shortwave radiation and directional shortwave radiation (Lindberg et al., 2008; Lindberg and Grimmond, 2011).

2.1.1. Shortwave radiation

The shortwave radiation K_i for each of the six directions depends on the sun position and has a direct (I) and diffuse (D) component. The direct shortwave radiation I on a horizontal surface can be calculated as the portion of extraterrestrial solar radiation $\bar{I}_0$ that travels through the atmosphere (VDI, 1994):

$$I_0 = \bar{I}_0 \cdot (1 + 0.03344 \cdot \cos((DOY \cdot 0.9856 - 2.72) \cdot \pi / 180^\circ)) \quad (3)$$

$\bar{I}_0$ is calculated using the solar constant $\bar{I}_0 = 1367 \text{ Wm}^{-2}$ and day of year (DOY) to determine the length of the path (the air mass) the radiation must travel. To consider atmospheric absorption and scattering of the incoming solar radiation, I can then be formulated as (Jendritzky, 1990):

$$I = I_0 \cdot \sin \eta e^{(-T_L \cdot \delta_{RO} \cdot m_{RO} \cdot \rho / \rho_0) \cdot (1 - N/8)} \quad (4)$$

where T_L is the Linke Turbidity factor (denotes the transparency of the cloudless atmosphere); ρ/ρ_0 is the pressure correction for reducing the optical thickness of the standard atmosphere at sea level (1013.25 hPa) to the current atmospheric pressure:

$$\rho = 101325 \cdot (1 - 2.25577 \cdot 10^{-5} \cdot z)^{5.25588} \quad (5)$$

N is degree of cloudiness in octas; δ_{RO} is the optical thickness (Kasten, 1980):

$$\delta_{RO} = 1 / (0.9 m_{RO} + 0.94) \quad (6)$$

m_{RO} is the relative optical air mass for a given sun elevation angle η (Kasten and Young, 1989):

$$m_{RO} = 1 / \left(\sin \eta + 0.50572 \cdot (\eta + 6.07995^\circ)^{-1.6364} \right) \quad (7)$$

Eq. (7) only holds for $\eta > 5^\circ$; for lower sun elevation angles, δ_{RO} has to be retrieved from a look-up table (Matzarakis et al., 2010).

The diffuse shortwave radiation D is composed of an isotropic (D_{iso}) and anisotropic (D_{aniso}) component and interpolated linearly between cloudless ($N = 0$) and overcast ($N = 8$) weather conditions (Matzarakis et al., 2010):

$$D = (D_{iso} + D_{aniso}) \cdot (1 - N/8) + 0.28 G_0 \cdot f_{SVF} \cdot N/8 \quad (8)$$

The isotropic component D_{iso} depends on the sky view factor f_{SVF} , the direct shortwave radiation I on a horizontal surface, the global radiation G_0 for $f_{SVF} = 1$ and cloudless conditions, and the transmittance of direct solar radiation τ :

$$D_{iso} = (G_0 - I(N = 0)) \cdot (1 - \tau) \cdot f_{SVF} \quad (9)$$

$$G_0 = 0.84 \cdot I_0 \cdot \cos \phi \cdot e^{\left(-0.027 \cdot \frac{\rho}{\rho_0} \cdot \frac{T_L}{\cos \phi} \right)} \quad (10)$$

$$\tau = I(N = 0) / (I_0 \cos \phi) \quad (11)$$

For shaded locations, the anisotropic component D_{aniso} is omitted; for sun-exposed locations, it is calculated as follows:

$$D_{aniso} = (G_0 - I(N = 0)) \cdot \tau \quad (12)$$

The sky view factor f_{SVF} is calculated from individual thermal panoramas assuming that all pixels with $T_s < 4^\circ\text{C}$ are sky pixels to distinguish them from urban surface pixels—a threshold that should be refined for other

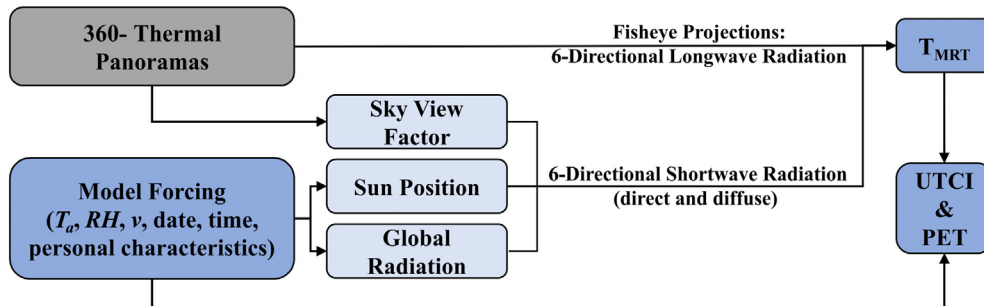


Fig. 1. *PanoMRT* model workflow including input (360° equirectangular thermal panorama, standard weather information, latitude/longitude, date, time, personal characteristics) and output (T_{MRT} , $UTCI$, PET).

geographic locations and weather conditions. The panoramas are projected into hemispherical views, and each thermal fisheye is partitioned into n annular rings ($n = 32$) to calculate f_{SVF} by summing up the contribution of non-sky pixels in each ring:

$$f_{SVF} = \frac{\pi}{2n} \sum_{j=1}^n \sin\left(\frac{\pi(2j-1)}{2n}\right) \left(\frac{p_j}{t_j}\right) \quad (13)$$

where p_j/t_j is the ratio between the number of sky pixels to the total number of pixels in ring j (Middel et al., 2017, 2018; Steyn, 1980). The hemispherical fisheye is further used to determine if a position is shaded or sun-exposed at any given time by determining the sun position in the fisheye and calculating the percent sky vs. non-sky pixels in a 3-by-3 pixel neighborhood.

To calculate the total shortwave radiation K including direct and diffuse radiation, we consider each of the six directions separately and use a simplified formulation by Lindberg and Grimmond (2011). The incoming shortwave radiation $K_{\downarrow}$ from the upper hemisphere is a function of the direct solar radiation on the plane normal to the direction of incidence $I' = I/\sin \eta$ and the diffuse radiation D (ignoring reflections from surfaces in the surroundings):

$$K_{\downarrow} = I' \cdot \sin \eta + D = I + D \quad (14)$$

The outgoing shortwave radiation $K_{\uparrow}$ is calculated as a fraction of the incoming shortwave, assuming that all surrounding surfaces are sun-exposed and have an average albedo of $\alpha = 0.20$:

$$K_{\uparrow} = K_{\downarrow} \cdot \alpha \quad (15)$$

The lateral reflected shortwave radiation is calculated as $K_{\rightarrow} = K_{\uparrow} \cdot \alpha \cdot 0.5$ for sun-exposed locations, ignoring reflections from vertical features and

assuming that all ground surfaces in the surrounding are sun-exposed (view factor of the ground is 0.5 in lateral fisheye views). The incoming lateral shortwave radiation depends on the cardinal direction (N, E, S, W) and will only be calculated for the two directions in which the sun is visible in the lateral fisheye projection, i.e.,

$$N : \theta \geq 270^\circ \quad K_{\rightarrow} = I' \cdot \cos \eta \cdot \sin(\theta - 270^\circ) + D \quad (16)$$

$$N : \theta < 90^\circ \quad K_{\rightarrow} = I' \cdot \cos \eta \cdot \sin(\theta + 90^\circ) + D \quad (17)$$

$$E : 0^\circ \leq \theta < 180^\circ \quad K_{\rightarrow} = I' \cdot \cos \eta \cdot \sin \theta + D \quad (18)$$

$$S : 90^\circ \leq \theta < 270^\circ \quad K_{\rightarrow} = I' \cdot \cos \eta \cdot \sin(\theta - 90^\circ) + D \quad (19)$$

$$W : 180^\circ \leq \theta < 360^\circ \quad K_{\rightarrow} = I' \cdot \cos \eta \cdot \sin(\theta - 180^\circ) + D \quad (20)$$

If θ falls outside the given range or the location is shaded, $I' = 0$.

2.1.2. Longwave radiation

Longwave radiation fluxes L_i in six directions are calculated from equirectangular thermal panoramas. To mirror a 6-directional net radiometer setup, the panoramas are projected into six fisheye views (Fig. 2) by relating pixels (x_p, y_p) of a $W \times H$ sized panorama to pixels (x_f, y_f) of a fisheye view with center pixels (C_x, C_y) using the following transformation:

$$x_p = \begin{cases} \left(\frac{\pi}{2} + \tan^{-1} \left[\frac{(y_f - C_y)}{(x_f - C_x)} \right] \right) \cdot W / 2\pi, & x_f < C_x \\ \left(\frac{3\pi}{2} + \tan^{-1} \left[\frac{(y_f - C_y)}{(x_f - C_x)} \right] \right) \cdot W / 2\pi, & x_f > C_x \end{cases} \quad (21)$$

$$y_p = H \cdot W / 2\pi \left(\sqrt{(x_f - C_x)^2 + (y_f - C_y)^2} \right) \quad (22)$$

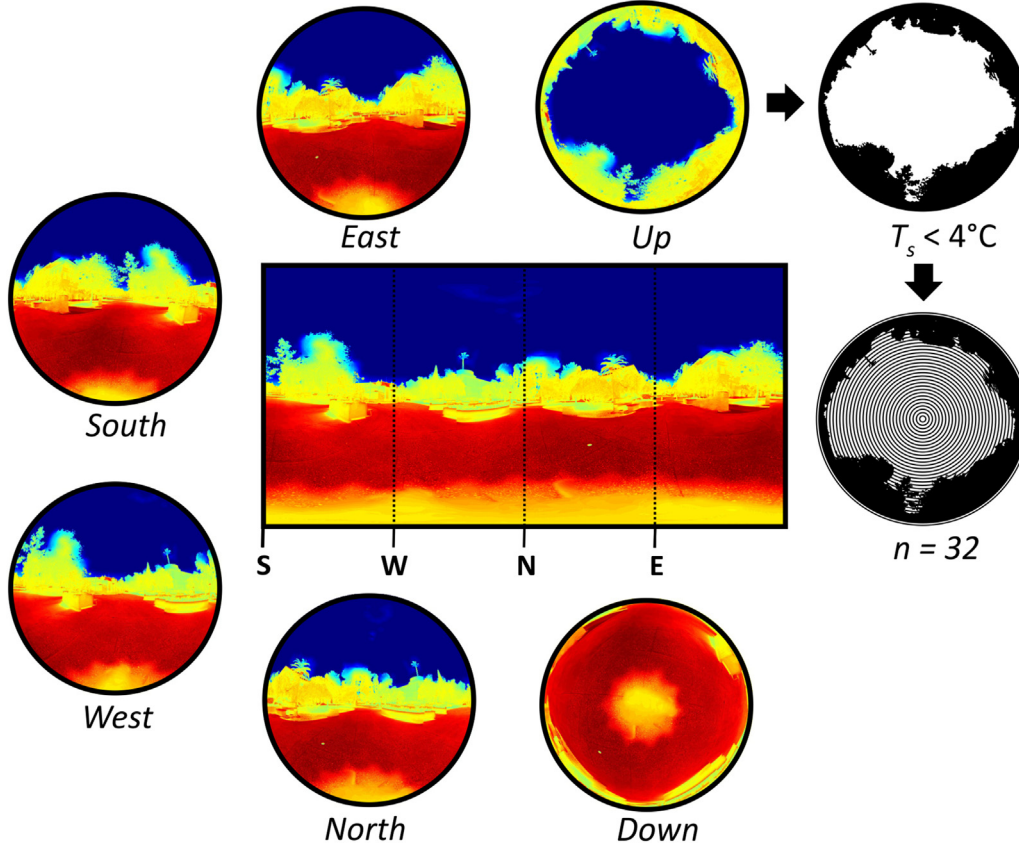


Fig. 2. Thermal panorama projection into 6-directional fisheye views; sky detection in thermal fisheyes using a threshold of $T_s < 4^\circ \text{C}$; and sky view factor (f_{SVF}) calculation using 32 annulus rings.

For each directional thermal fisheye, T_s of non-sky pixels is converted to a longwave radiation flux assuming a standard emissivity of $\epsilon = 0.95$ and atmospheric radiation A as follows:

$$L_{\text{pixel}} = \epsilon \sigma (T_s + 273.15)^4 + (1 - \epsilon) \cdot A \quad (23)$$

$$A = \sigma \cdot (T_a + 273.15)^4 \cdot (0.82 - 0.25 \cdot 10^{-0.0945 \cdot V_p}) \cdot \left(1 + 0.21 \cdot (N/8)^{2.5}\right) \quad (24)$$

Longwave radiation for sky pixels is estimated from T_a and sky emissivity ϵ_{sky} , which is a function of vapor pressure V_p and T_a (Lindberg et al., 2008):

$$L_{\text{sky}} = \epsilon_{\text{sky}} \sigma (T_a + 273.15)^4 \quad (25)$$

$$\epsilon_{\text{sky}} = 1 - \left(1 + 46.5 \frac{V_p}{T_a + 273.15}\right) \cdot e^{\left(-\left(1.2 + 3.0 \cdot 46.5 \frac{V_p}{T_a + 273.15}\right)^{0.5}\right)} \quad (26)$$

Finally, L_i is calculated for each directional thermal fisheye by summarizing average longwave radiation values over 32 annulus rings (analogous to the f_{SVF} calculation) and inserted in Eq. (2) along with the directional shortwave radiation fluxes K_i (Eqs. (14)–(20)) to yield the mean radiant flux density R and subsequently T_{MRT} .

2.2. Thermal comfort index calculations

Thermal comfort is a complex function of environmental factors determining thermal exposure and physiological, psychological, and behavioral factors (Chen and Ng, 2012; Johansson et al., 2014; Middel et al., 2016; Nikolopoulou and Lykoudis, 2006). Numerous thermal comfort indices have been developed to integrate environmental and personal factors into an experienced temperature value (Potchter et al., 2018). The current implementation of *PanoMRT* calculates *PET* (Höppe, 1999) and *UTCI* (Blázquez et al., 2012; Fiala et al., 2012; Jendritzky et al., 2012) based on user-configured personal characteristics (age, gender, height, weight), metabolic rate, and clothing insulation.

3. Model validation

PanoMRT was validated through in-situ observations of human-biometeorological data at the time of thermal panorama acquisition. Model performance was assessed using standard model statistics such as the Root Mean Square Error (RMSE), Mean Bias Error (MBE), and the index of agreement (d) (Willmott, 1982). In addition, *PanoMRT* results were compared to *RayMan* (Matzarakis et al., 2010) simulations to assess the benefit of spatially explicit T_s observations for location-based T_{MRT} modeling. For this comparison, *RayMan* was run with hemispherical black and white images generated from the thermal panoramas (assuming a threshold of 4 °C for sky pixels) and the same meteorological forcing as *PanoMRT* (observed T_a and RH but not T_s). Lastly, *PET* and *UTCI* were calculated from human-biometeorological observations (T_a , T_{MRT} , RH , v) and default parameters for personal characteristics for *PET* (35-year old male, 1.75 m, 75 kg, clothing insulation 0.5 clo, metabolic rate 80 W m^{-2}) for comparison to *PanoMRT* and *RayMan* results to determine the impact of spatially explicit T_s on thermal index calculations.

3.1. Study site

PanoMRT was developed, tested, and validated in hot and dry Tempe, Arizona, USA. Tempe is situated in the East Valley of the Phoenix metropolitan area, a region in the Sonoran Desert of the U.S. Southwest with low annual rainfall (237 mm) and low relative humidity (Köppen Climate Classification subtype *Bwh*). With an average of 300 clear, sunny days per year, air temperature peaks at or above 32 °C for an average of 175 days, and maximum air temperatures frequently surpass 43 °C in June. To test and validate *PanoMRT*, we chose 18 locations on Arizona State University's

Tempe campus that are within walking distance from each other to allow for transect observations (Fig. 3). The campus is a 2.6-km² area of interconnected pedestrian malls and can be considered an open midrise local climate zone (Stewart and Oke, 2012). We selected diverse sites with respect to ground cover (asphalt, concrete, grass), sky view factor (f_{SVF}), and shading (trees, building tunnel, engineered shade canopies, fully exposed). In addition, we conducted field observations on the Phoenix Zoo main parking lot, which is located 5 km north of campus and has minimal horizon limitation ($f_{\text{SVF}} = 0.98$).

3.2. Thermal panorama retrieval and T_{MRT} observations

Thermal panoramas were acquired on campus along with in-situ observations of human-biometeorological data on three hot, dry, clear summer days in summer 2020: May 27, May 28, and June 16. Observational walking transects were conducted every 3 h from 6:00 h to 20:00 h local time covering five to six locations per day. The Phoenix Zoo parking lot location was monitored hourly on June 3, 2020 from 7:00 h to 17:00 h.

A FLIR Duo Pro R Dual-Sensor 4K Thermal Camera (640 × 512 pixels, 45° horizontal field of view) was attached to a Gigapanos rotational arm on a tripod to automatically capture a matrix of 8 × 10 visual and thermal images with 25 % overlap at each location (Fig. 4b). A complete 360° scan took about 5 min. In post-processing, the sets of visual images were arranged in a grid and stitched into an equirectangular panorama using the stitching software PTGUI. The stitching parameters then served as a template for creating the corresponding thermal panoramas (Fig. 5).

T_{MRT} was observed at each location using the mobile weather station *MaRTy* (Middel et al., 2021; Middel and Krayenhoff, 2019). *MaRTy* is a human-biometeorological instrument platform that records 6-directional radiation flux densities (L_i and K_i), T_a , horizontal wind speed (v), and relative humidity (RH) at 2 s intervals (Fig. 4a). The platform was placed in the center of the panorama tripod location immediately after each thermal scan to collect human-biometeorological data for 1–2 min. The first 15 records at each location were removed to account for the response time of the T_a/RH probe (sensor time constant 22 s, 63 % step change) and minimize the impact of sensor lag (Häb et al., 2015); the remaining records were averaged for each location and time to provide localized forcing data for the *PanoMRT* validation (T_a , RH , v) and T_{MRT} ground truth.

3.3. Results

3.3.1. Meteorological conditions and in-situ observations

Meteorological conditions were similar across field work days with minimum T_a between 24 °C and 31 °C, maximum T_a between 41 °C and 43 °C, and clear, sunny skies. RH ranged between 21 % and 25 % at 6:00 h and below 10 % during the afternoon hours. Wind speed was generally low ($<1.0 \text{ m s}^{-1}$ on average across all observations) with peak gusts of up to 4.3 m s^{-1} .

T_{MRT} varied considerably across locations and times of day, especially between sun-exposed and shaded sites (Fig. 6). T_{MRT} peaked in the afternoon (between 15:00 h and 16:00 h) at open locations with high f_{SVF} , such as the sun-exposed parking lot location 10 ($f_{\text{SVF}} = 0.84$) with 72.3 °C and the concrete path intersection 12 ($f_{\text{SVF}} = 0.81$) with 71.0 °C. In contrast, T_{MRT} was close to T_a during the day under large, dense shade trees (locations 4, 16, and 2) and below T_a inside a tunnel through a parking garage (location 8). After sunset, T_{MRT} was highest in a narrow east-west canyon enclosed by concrete walls (location 6, 35.6 °C), under a metal shade structure (location 1, 35.6 °C), and inside the tunnel (location 8, 36.9 °C). Coolest T_{MRT} was recorded over grass after sunset (location 11, $f_{\text{SVF}} = 0.93$, 22.9 °C).

Surfaces showed the greatest variability in temperature across surface types, sun exposure level, and times of day. Irrigated grass exhibited the lowest T_s at 6:00 h with 19.8 °C (location 3) and 19.2 °C (location 11) and did not exceed T_a throughout the day. The hottest ground T_s in excess of 60 °C was recorded midday over a concrete path (location 12), an asphalt road (location 9), and the Phoenix Zoo asphalt parking lot (location 10).

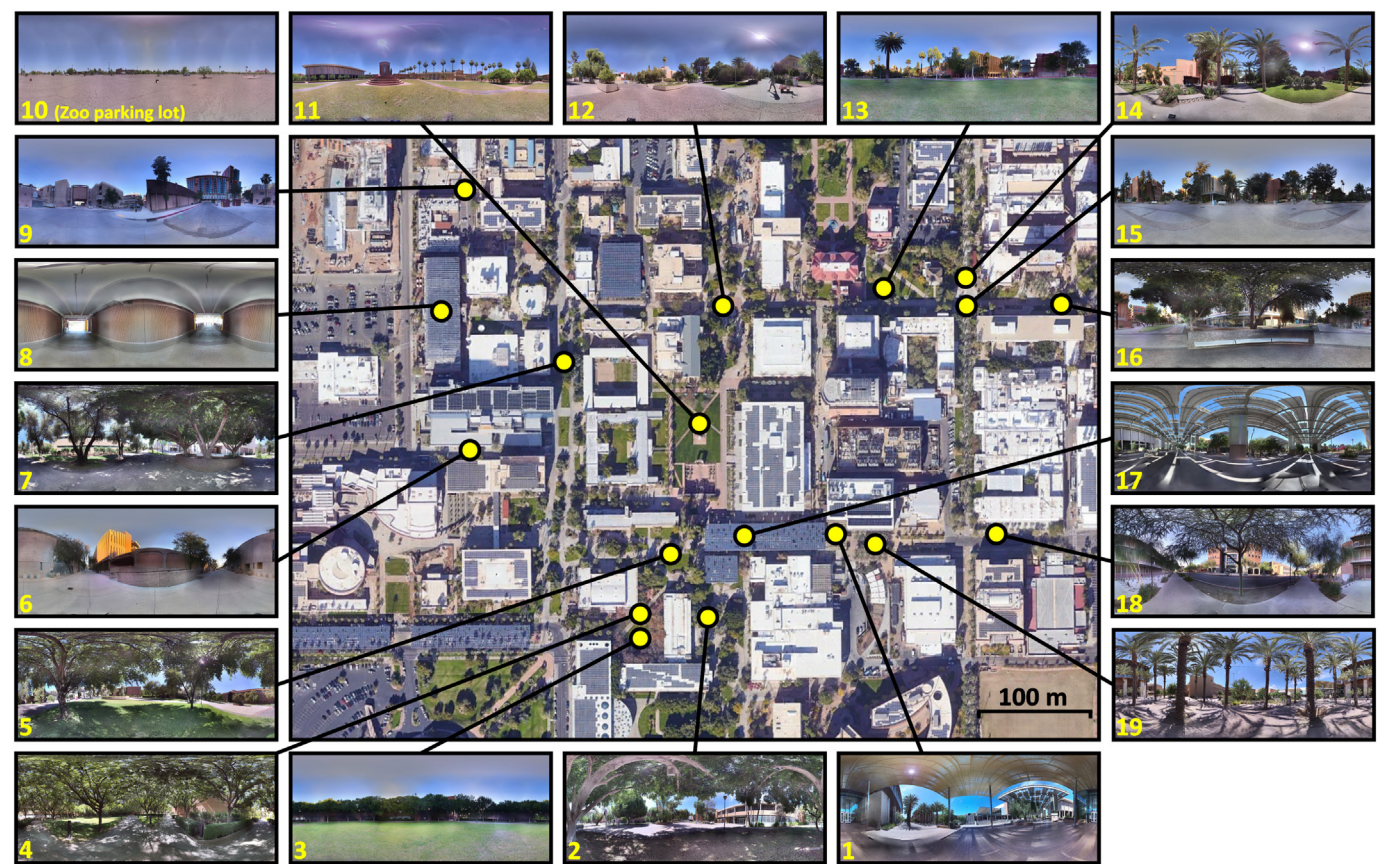


Fig. 3. Equirectangular panoramas of 18 observation sites on Arizona State University's Tempe campus and one site on the Phoenix Zoo parking lot (upper left panorama, location outside map 5 km north of campus). For site metadata (fisheye photos, exposure, ground cover, sky view factor) see Supp. Table 1.

The thermal panoramas illustrate the T_s distribution of surfaces in the 360° surroundings of each location (Fig. 7).

3.3.2. PanoMRT and RayMan model performance

PanoMRT performs well overall (Supp. Table 3) with a Root Mean Square Error (RMSE) of 4.1 °C for all observations ($N = 145$), which meets the accuracy requirement of ± 5 °C set in the ISO 7726 standard

(ISO, 1998) for heat and cold stress studies. The model exhibits an unsystematic RMSE of 4.5 °C and a systematic RMSE of 0.7 °C, indicating that model parameters are well-specified and the majority of the error results from processes or model-observation differences beyond the scope of the current model. This includes errors associated with observation procedures and instrumentation setup: human-biometeorological observations and thermal panoramas were not taken at the same time but successively, and

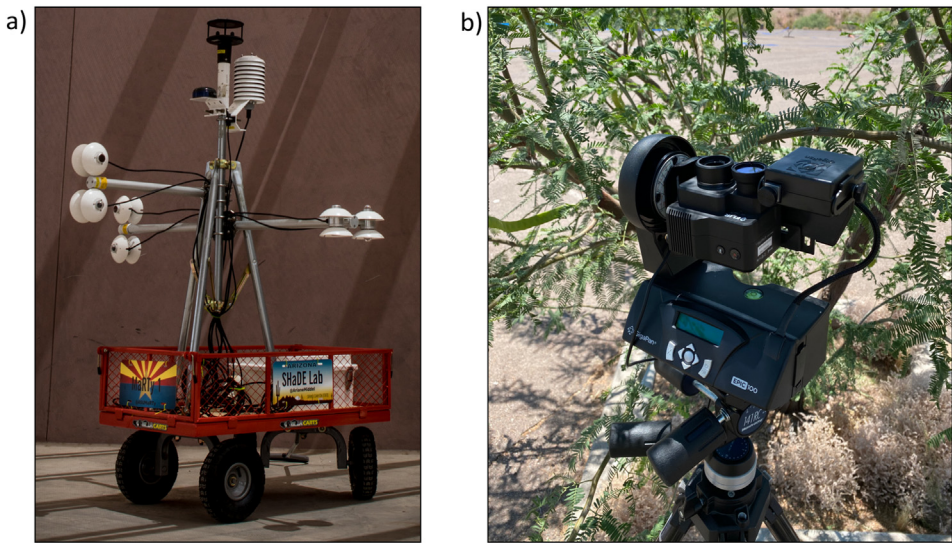


Fig. 4. a) Mobile human-biometeorological instrument platform MaRTy (Middel et al., 2021; Middel and Krayenhoff, 2019); b) FLIR Duo Pro R Dual-Sensor 4K Thermal Camera on a Gigapan rotational arm. For instrument specifications see Supp. Table 2.

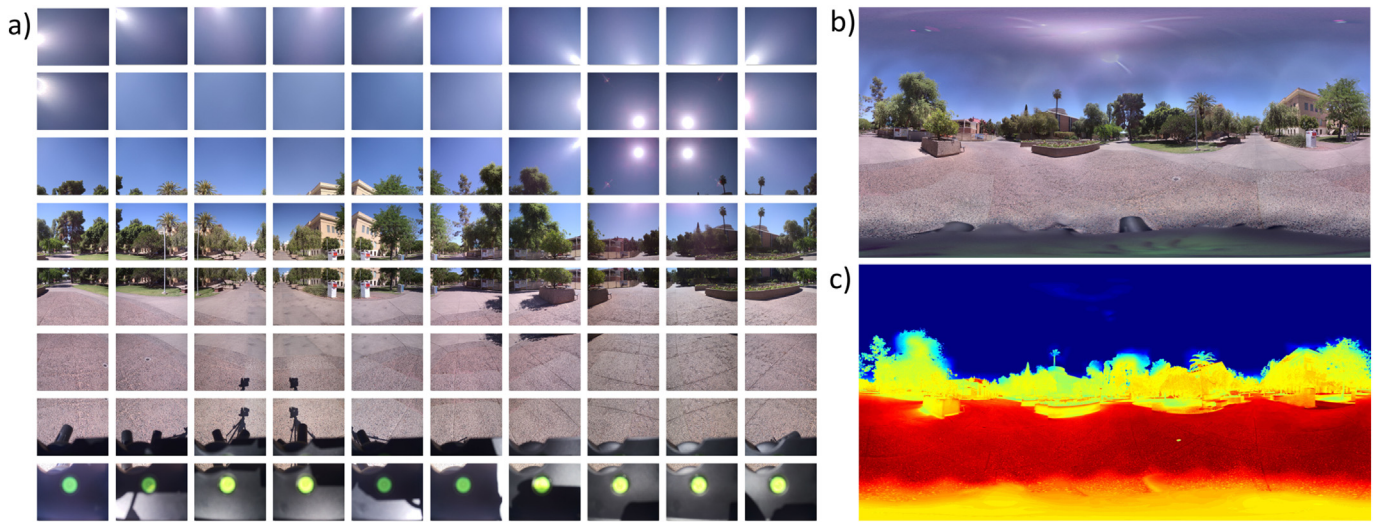


Fig. 5. a) Matrix of 8×10 overlapping photos from panorama scan at location 12; b) stitched visual panorama; c) corresponding stitched thermal panorama.

MaRTy's net radiometers are subject to varying spatial exposure, because they are 0.6–1.0 m apart. The Mean Bias Error (*MBE*) captures the average bias in the prediction and is negative (-1.9°C), meaning that *PanoMRT* tends to underestimate T_{MRT} . The slope of the regression line (Supp. Fig. 1) supports this observation. The Mean Absolute Error (*MAE*), i.e. the sum of absolute errors divided by the sample size, is 3.2°C , and the index of agreement (*d*), i.e. a standardized measure of the degree of model prediction error, shows excellent agreement with $d = 0.98$.

PanoMRT performance varies by time of day (6:00 h, 9:00 h, 12:00 h, 15:00 h, 18:00 h, 20:00 h), exposure (sun/shade), and shade type (tree/engineered) (Fig. 8). The lowest *RMSE* (3.3°C) is observed at 20:00 h when incoming shortwave radiation is zero and the model solely relies on the measured thermal panorama input. At this time of day, errors can be attributed to an assumed fixed emissivity (0.95) for the thermal images, the assumption that reflected longwave from surfaces originates from the sky only, inaccuracies in the sky detection at the transition between the built environment and sky, and the tripod surface temperature, which is in the field of view of the camera and obstructs parts of the ground. In addition, the model tends to underestimate T_s for sky pixels and therefore L for open sites with a large f_{SVF} (overall *RMSE* = 3.8°C , *MAE* 3.0°C , $d = 0.93$). Model results after sunrise (6:00 h) exhibit the highest *RMSE* (5.0°C) with a negative *MBE* (-2.3°C). *PanoMRT* underestimates incoming solar radiation at low sun angles, and meteorological conditions change quickly after sunrise, which introduces differences in *MaRTy* and thermography observations that impact model validation and add to unsystematic errors. The model performs equally well for engineered shade (*RMSE* = 4.2°C) and tree shade (*RMSE* = 4.1°C) due to available surface temperature observations for both shade types from thermal panoramas. Systematic errors are low for all times of day, exposures, and shade types. The largest *RMSEs* is observed at noon with 3.1°C , otherwise *RMSEs* ranges between 0.7°C and 1.6°C .

PanoMRT performance also varies by location due to heterogeneous urban forms. A majority of sites (120 of 145 observations across space and time) exhibit a $<5^\circ\text{C}$ difference between modeled and observed T_{MRT} , and more than half (75) of the modeling results are within 3°C of the *MaRTy* observations. Two sites show large discrepancies in the morning: T_{MRT} at location 18 (under a Palo Verde tree, $f_{SVF} = 0.17$) is overestimated by 11.2°C during the 9:00 h transect, and T_{MRT} at location 15 (sun-exposed concrete crossing, $f_{SVF} = 0.87$) is overestimated by 11.2°C during the 6:00 h transect. Both observations are subject to measurement errors as one of *MaRTy*'s net radiometers was inadvertently shaded. In contrast, *PanoMRT* significantly underestimates T_{MRT} for locations 11 (lawn next to Arizona State University's Hayden library, $f_{SVF} = 0.85$) at 18:00 h, 1 (metal shade structure, $f_{SVF} = 0.10$) at 16:00 h, and

17 (photovoltaic shade structure, $f_{SVF} = 0.04$) at 12:00 h. The difference in modeled and observed T_{MRT} of -10.8°C for location 11 is due to the low sun elevation angle that leads to underestimated incoming shortwave radiation in the model. T_{MRT} estimation errors under engineered shade result from inadvertent sun exposure of a net radiometer due to the off-center placement of the sensors. Overall, the most challenging location for *PanoMRT* to estimate T_{MRT} is 19 ($f_{SVF} = 0.37$), which is a plaza surrounded by tall palm trees. The model is unable to handle semi-shade or dappled shade and underestimates T_{MRT} by -5.6°C to -7.6°C when the sun is not visible in the upper hemisphere (obstructed by palm leaves, shaded) and overestimates T_{MRT} by 5.8°C for the sun-exposed case at 12:00 h.

RayMan has an overall *RMSE* of 9.0°C (Supp. Table 3) with an unsystematic *RMSE* of 7.8°C (mostly due to observation procedures and instrumentation setup) and a systematic *RMSE* of 4.4°C . The *MBE* for all observations ($N = 145$) is positive, indicating that *RayMan* tends to overestimate T_{MRT} . The *MAE* is 7°C , and the index of agreement shows good overall model performance ($d = 0.89$).

RayMan performance varies significantly by time of day, exposure, and shade type (Fig. 8). The lowest *RMSE* is observed after sunset (3.2°C). Model results at 12:00 h and 15:00 h exhibit the highest *RMSE* (11.0°C and 11.4°C), the highest *MAE* (8.5°C and 10.6°C), and the lowest d (0.42 and 0.51). During mid-day, I and T_s peak, therefore modeling errors in emitted longwave radiation are expected to be largest. With respect to exposure, the *MBE* shows that *RayMan* overestimates shaded locations and underestimates sun-exposed locations. In the shade, the *RMSE* is 11.8°C for trees and 9.2°C for engineered shade, respectively, due to overestimation of surrounding T_s . In the sun, the *RMSE* amounts to 8.2°C . The absence of reflected shortwave radiation in the model is likely a contributing factor to underestimated T_{MRT} values in sun-exposed locations.

RayMan performance varies significantly by location. Simulations are most accurate for open sites with high f_{SVF} . Half of the modeling results are within 5°C of T_{MRT} observations, while only 46 model runs yield T_{MRT} results within 3°C of *MaRTy* observations. Locations 8 (tunnel, $f_{SVF} = 0.00$), 7 (dense tree canopy cover, $f_{SVF} = 0.02$), 2 (dense tree canopy cover, $f_{SVF} = 0.02$), and 4 (medium dense tree canopy cover, $f_{SVF} = 0.32$) exhibit the largest T_{MRT} error of up to -24.9°C , -19.3°C , -18.1°C , and -17.2°C respectively, during the 12:00 h transect. T_{MRT} is overestimated at all times at the four locations due to a modeling error of shaded T_s of up to 8.8°C , which translates into overestimated longwave emission.

In contrast, *RayMan* underestimates T_{MRT} by up to -17°C for open locations 13 (lawn next to Arizona State University's Old Maine, $f_{SVF} = 0.84$) and 12 (sun-exposed concrete crossing, $f_{SVF} = 0.87$) at low sun angles

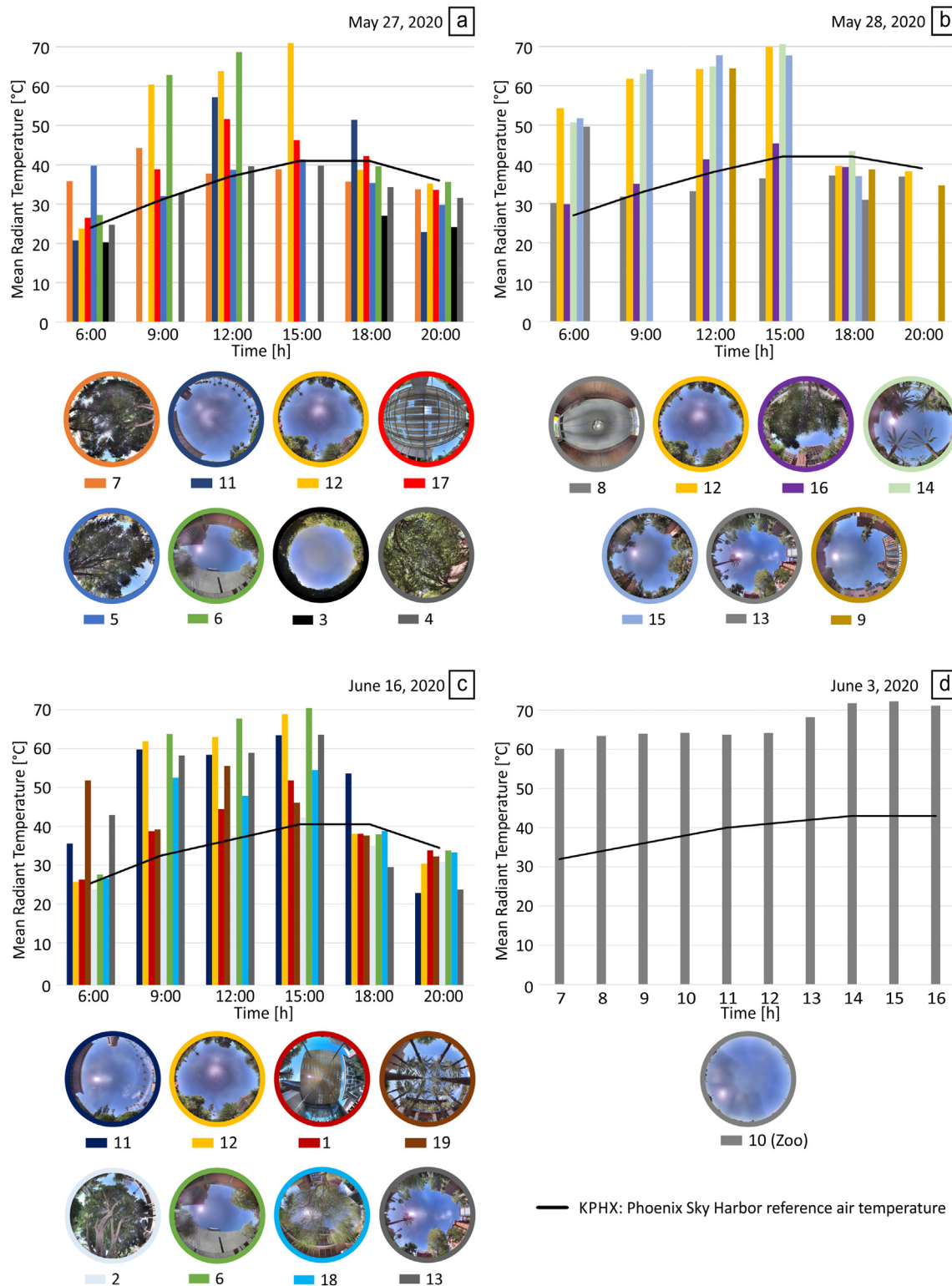


Fig. 6. In-situ mean radiant temperature observations with MaTy for all field work days and locations: a) May 27, 2020; b) May 28, 2020; c) June 16, 2020; d) June 3, 2020.

during the 6:00 h transect. Some of these errors are due to inaccuracies in the fisheye photo where the pixel of the calculated sun position is black (i.e. the location is shaded) but the neighboring pixels are white, and the observations are actually sun-exposed (or vice versa, *RayMan* models sun-exposure for a shaded location). Analogous to *PanoMRT*, *RayMan* struggled to model the semi-shade of location 19 (plaza with tall palm trees, $f_{SVF} = 0.37$), and measurement errors due to accidental sun or shade exposure of

one of *MaTy*'s net radiometers led to inadvertent differences in modeled and observed T_{MRT} for locations 18, 15, 17, and 1.

3.3.3. Mean radiant temperature error propagation into thermal indices

Since *PET* and *UTCI* are driven by T_{MRT} , modeling errors related to radiative heat fluxes propagate into *PET* and *UTCI* outcomes. Here, temperature, humidity, and wind speed are provided by the *MaTy*

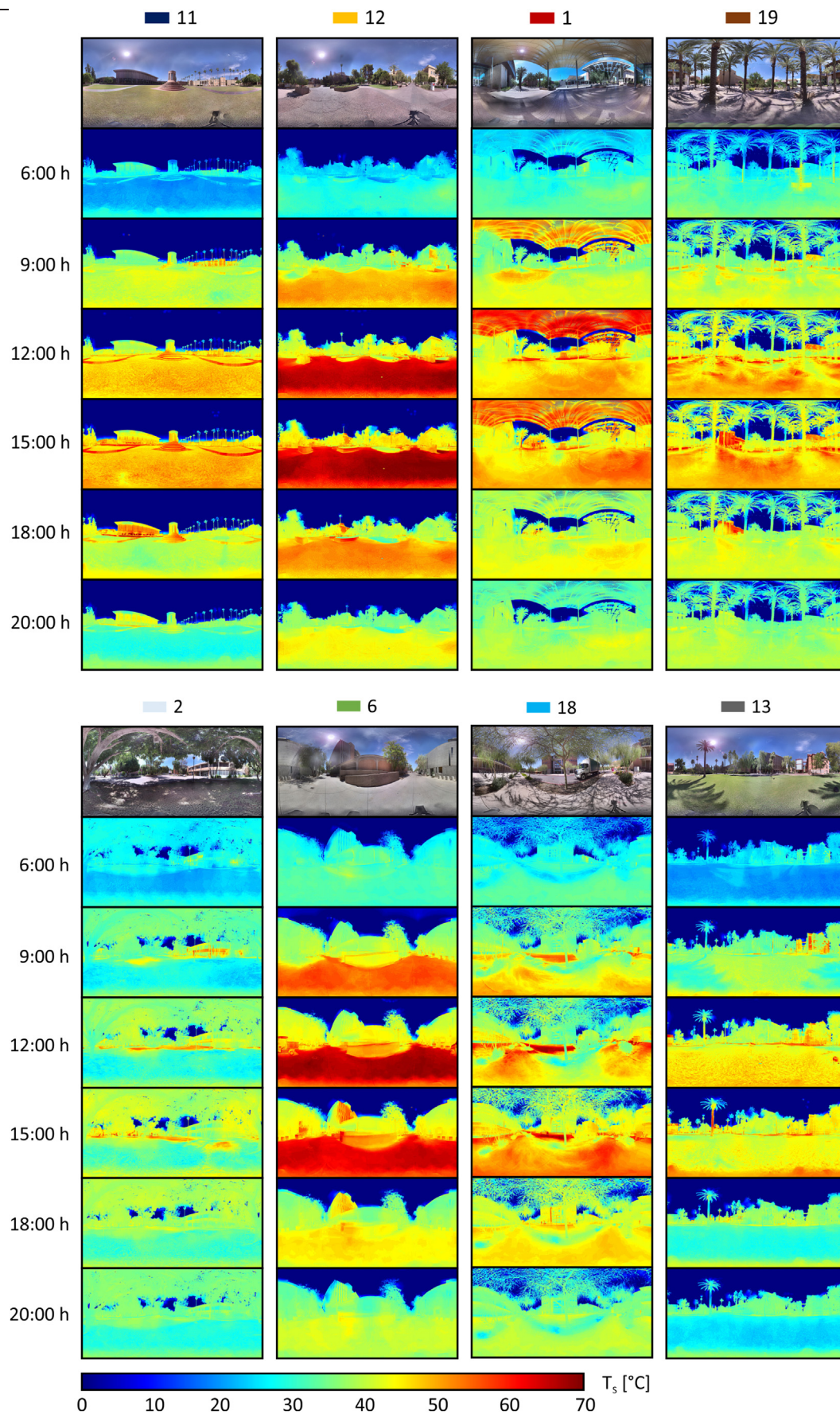


Fig. 7. Thermal panoramas for all locations observed on June 16, 2020: after sunrise (6:00 h), mid-morning (9:00 h), midday (12:00 h), midafternoon (15:00 h), before sunset (18:00 h), after sunset (20:00 h).

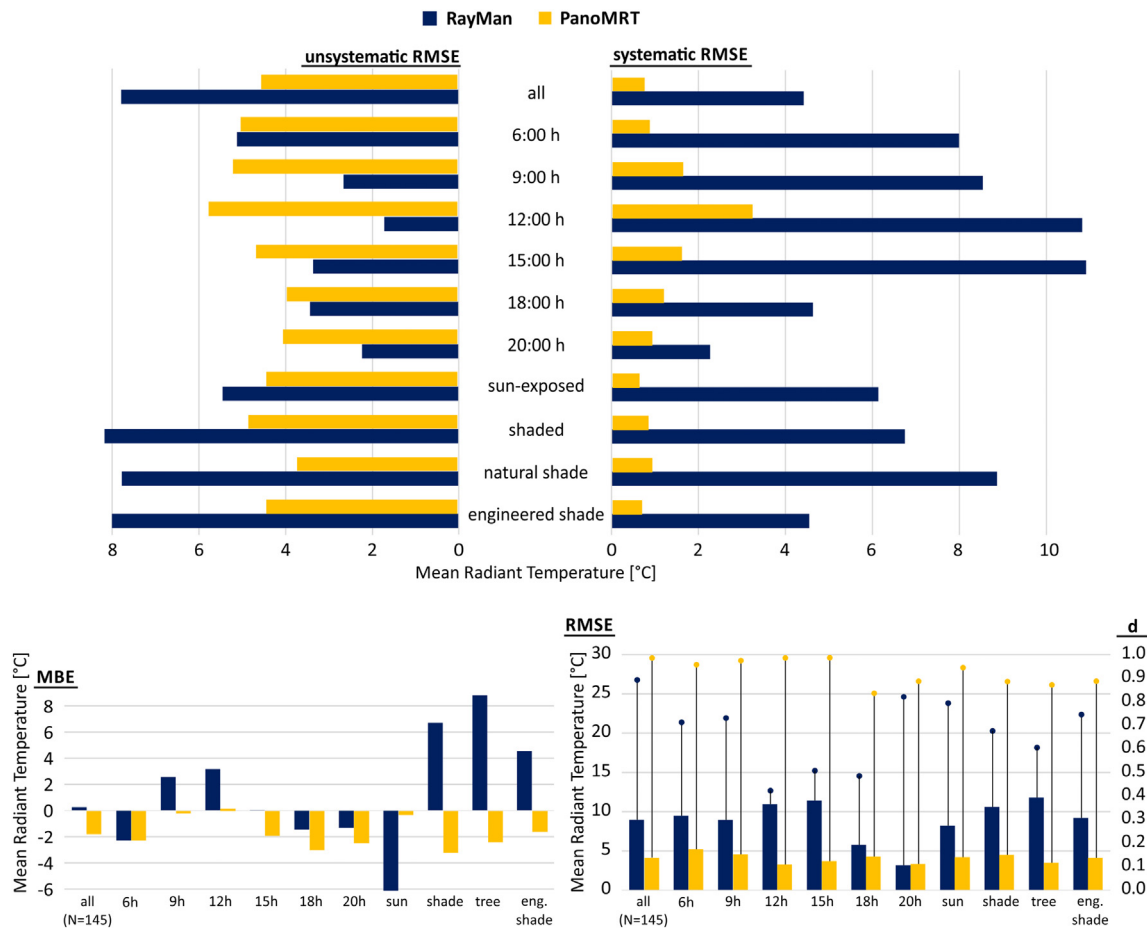


Fig. 8. Model performance statistics for *PanoMRT* and *RayMan* including Root Mean Square Error (*RMSE*), unsystematic *RMSE* (*RMSEu*), systematic *RMSE* (*RMSEs*), index of agreement (*d*), and Mean Bias Error (*MBE*). R^2 values are illustrated in Suppl. Fig. 1–3. Violin plots of *PanoMRT* model errors are shown in Suppl. Fig. 4. Performance statistics are summarized in suppl. Table 3.

biometeorological station, and therefore all errors in *PET* and *UTCI* derive from T_{MRT} modeling. *PanoMRT* results for *PET* yield an overall *RMSE* of 2.6 °C with an *MAE* of 2.2 °C, *MBE* of −1.53 (model tends to underestimate *PET*), and *d* of 0.97. Reference *RayMan* simulations without T_s forcing have an *RMSE* of 6.4 °C with an *MAE* of 5.3 °C, *MBE* of 4.80 (model tends to overestimate *PET*), and *d* of 0.85. Concurrent with T_{MRT} estimates, model results for *PET* meet the accuracy requirement of ± 5 °C set in the ISO 7726 standard for heat and cold stress studies when spatially explicit T_s are used as model input. *UTCI* is less sensitive to T_{MRT} and T_s of the built environment. *PanoMRT* models *UTCI* with an *RMSE* of 1.22 °C and *RayMan* with an *RMSE* of 2.31 °C.

4. Discussion

Since *PanoMRT* and *RayMan* have similar procedures to calculate incoming shortwave radiation, forcing both models with *MaRTy* observed human-biometeorological data and comparing results allows to quantify the benefit of using spatially explicit, human-centric, 3-dimensional T_s (T_{ped}) for T_{MRT} modeling. *RayMan* exhibits larger errors than *PanoMRT* for all times, exposures, and shade types except at 20:00 h when *RMSE* is similar (3.2 °C and 3.3 °C). Overall, thermal panoramas reduce *RMSE* from 9.0 °C to 4.1 °C, which meets the accuracy requirement of ± 5 °C set in the ISO 7726 standard. The biggest model performance boost is observed at 12:00 h when T_s are highest. *RMSE* improves from 11.0 °C to 4.0 °C while *d* increases from 0.42 to 0.97. Previous studies confirm that *RayMan* overestimates T_s for enclosed sites, especially during the summer, which results in a large positive *MBE* for shaded sites with low f_{SVF} (Colter et al., 2019; Crank et al., 2020; Gál and Kántor, 2020; Krüger et al., 2014; Lee and

Mayer, 2016). While sun exposure is the main driver of variability in T_{MRT} under clear sky conditions (Lee et al., 2014; Lindberg et al., 2016), longwave fluxes gain importance in denser built environments (Lindberg et al., 2014). Middel and Krayenhoff (2019) found that lateral components of the longwave flux are the largest contribution to T_{MRT} , rendering T_s of the surrounding built environment the second most important input variable after sun exposure for accurate T_{MRT} modeling as evidenced in the performance improvement reported here. Spatially explicit T_s forcing also enhances *PET* and *UTCI* calculations, but *PET* is more sensitive to accurate T_s input than *UTCI*.

As for all image based T_{MRT} models, *PanoMRT* and *RayMan* are sensitive to the location of photo acquisition (fisheye image or panorama) in complex urban geometries. Sun exposure may be miscalculated due to pixel misalignment, especially at the transition from horizon limitation to sky and in tree canopies. For some locations, our model evaluation was further impacted by observation procedures and instrumentation setup. *MaRTy* observations were taken after the thermal panorama was acquired, not concurrently, and in a few instances, one of *MaRTy*'s net radiometers was inadvertently exposed to the sun or shade. Those observational flaws contribute to the unsystematic error in both models and do not bias the model results.

PanoMRT is not the first T_{MRT} model based on thermal photography. Several approaches have been developed in recent years, most of which are restricted to indoor settings. Lee et al. (2019) developed a system using angle factors and an infrared thermal camera to model T_{MRT} for large stadiums. Their setup overestimated T_{MRT} by 0.9 °C with $R^2 = 0.83$ compared to globe thermometer observations and was subsequently improved to a pan-tilt scanning system (Lee and Jo, 2021). Initial tests of

the system in indoor and longwave-dominated outdoor settings yielded an R^2 of 0.80 (Lee and Jo, 2022). Natephra et al. (2017) integrated thermal images with 3-dimensional Building Information Models (BIMs) to investigate the performance of building envelopes and occupancy comfort levels but did not provide performance statistics. More recently, Acuña Paz y Miño et al. (2020) developed the “4 π ” method to evaluate outdoor radiant environments using photographic high dynamic range (HDR) images and longwave infrared images. The resulting short- and longwave radiance maps yielded T_{MRT} values within 2 °C of globe temperature readings for 15 observations that were conducted in France and Spain during mostly cloudy winter conditions and at night, so impacts of direct shortwave radiation were minimal. In contrast, Merchant et al. (2022) collected longwave and shortwave panoramas under clear sky, hot, dry conditions in Tempe, Arizona using a SMaRT-SL sensor platform and report a significant improvement over the previous version of the system, which relied on thermal point clouds (Aviv et al., 2021). Their analysis mainly focused on comparing directional short- and longwave panoramas to a 6-directional net radiometer setup but findings suggest that integrating those fluxes into T_{MRT} would yield accurate results.

PanoMRT is in development and has several limitations with respect to shortwave and longwave calculations. The model currently underestimates longwave radiation for sky pixels, i.e. T_{MRT} is underestimated for sites with high f_{SVF} . In addition, the threshold to determine sky pixels (4 °C) works well for clear hot dry summer conditions but needs to be adjusted for other meteorological conditions, seasons, and geographic locations. For example, Asawa et al. (2022) manually determined 10 °C and 18 °C as appropriate sky pixel thresholds for a thermal imaging system in Tokyo. Alternatively, sky pixels could be detected automatically from the visible photographs that are used to determine the stitching parameter for the thermal images. Image segmentation approaches using convolutional neural networks to identify sky pixels have gained popularity in recent years and can also handle cloudy conditions (Middel et al., 2019; Nice et al., 2020; Zeng et al., 2018).

At sun-exposed locations, *PanoMRT* assumes an average albedo of 0.20 for the surrounding surfaces to calculate reflected shortwave radiation. Reflected shortwave contributions are likely overestimated, because the model assumes equal reflection from all solid surfaces, even shaded surfaces, when the location is sun exposed. This yields a “worst-case” T_{MRT} for sun-exposed locations. Similarly, reflected shortwave radiation is assumed to be zero for shaded locations and therefore underestimated. While this approach simplifies exposure of the complex built environment (e.g. in reality, parallel building walls are not simultaneously exposed), the impact of T_{MRT} is <1 °C. Longwave radiation in Phoenix is the largest contributor to T_{MRT} (Middel and Kravenhoff, 2019), and the impact of sun exposure on surface temperatures is directly captured through the thermal panoramas. Merchant et al. (2022) observed reflected shortwave radiation in the built environment using a SMaRT-SL shortwave array sensor that produces panoramic views of shortwave radiant heat fluxes and found that reflected shortwave radiation can be on the order of 100 Wm⁻² during midday. Most microclimate models that do account for reflection use raytracing and view factors of surface patches to estimate reflected shortwave radiation (Kravenhoff and Voogt, 2007; Lachapelle et al., 2022; Lindberg et al., 2016; Simon et al., 2021). A similar approach could be incorporated into *PanoMRT* using image segmentation to detect various surface types and assign appropriate radiative and thermal properties to each pixel. Classified surface types would also be required to estimate view factors of buildings and vegetation in each direction to refine the calculation of D (Eqs. (16)–(20)) as implemented by (Lindberg et al., 2008).

Currently, *PanoMRT* assumes that the thermal panoramas are corrected for emissivity. An appropriate correction for target emissivity is required for accurate T_s measurements, because T_s of an object may appear to be emitting more radiation than it really is, for example, a metal bench. Our validation sites were chosen to not have extensive surfaces with low emissivity in the surrounding to minimize the impact of emissivity on the results.

Lastly, *PanoMRT* cannot model dappled or partial shade because sun exposure is modeled in a true/false fashion with no option to define shade transmissivity. This leads to inaccurate T_{MRT} estimates under trees with low leaf area density and engineered structures such as photovoltaic canopies and cloth umbrellas. Konarska et al. (2014) measured the transmissivity of total and direct solar radiation through foliated and leafless tree crowns in Göteborg, Sweden and found a wide transmissivity range from 1.3 % to 51.9 %. Results were incorporated into the SOLWEIG model (Lindberg et al., 2008) to improve T_{MRT} calculations. Transmissivity estimates could be incorporated into *PanoMRT* by detecting overhead obstructions in the photographs and estimating transmissivity using sky versus non-sky pixels of the obstruction.

PanoMRT is a hybrid modeling approach that relies on T_s observations to calculate longwave radiation and models shortwave radiation based on the sun position and simple meteorological forcing. As it meets the accuracy requirement of ± 5 °C set in the ISO 7726 standard, it has the potential to be used in place of the 6-directional setup, which is considered the gold standard to measure T_{MRT} but is a major research expense (>\$20 k). Globe thermometers to measure T_{MRT} are more affordable (\$500) but have a slow response time and require precise heat loss estimates (Vanos et al., 2021). The current thermal panorama setup measures the surroundings in 2–3 min and could be improved further, e.g., by using a FLIR ONE camera attachment for phones that directly captures panoramas without the need for stitching. In summary, *PanoMRT* constitutes an affordable, practical alternative to current T_{MRT} acquisition and modeling approaches.

5. Conclusions

Mitigating urban overheating through urban design interventions (e.g., trees, cool pavement) is a top priority of the 21st century for cities around the world. Assessing the impacts of design changes on human thermal exposure requires fine-scale information on radiative heat fluxes in the built environment. We demonstrated the importance of human-centric, spatially explicit T_s data, i.e., approximated T_{ped} observations using panoramic thermography, for capturing complex longwave radiation patterns that result from a patchwork of surface types with varying orientation, diurnal sun-exposure, and material characteristics. *PanoMRT* model results show that T_{ped} measurements are most important during midday (peak T_s) and for shaded locations, because T_{ped} captures T_s underneath the shade in contrast to horizontal T_s from thermal satellite imagery. The use of spatially explicit T_s as model input improved T_{MRT} estimates such that they met the accuracy requirement of ± 5 °C set in the ISO 7726 standard for heat and cold stress studies. T_{MRT} modeling errors propagated into thermal comfort index calculations more strongly for *PET* than *UTCI* but significantly improved modeling accuracy for both indices, indicating that T_{ped} is also highly relevant to human thermal comfort assessments. T_s has long been recognized as key parameter in urban climate, but traditional acquisition methods lack spatial resolution and do not capture pedestrian-relevant surfaces patches. Our work elevates the importance of human-centric, street-level T_s measurements for thermal exposure assessments.

CRedit authorship contribution statement

AM: Conceptualization, Methodology, Validation, Formal Analysis, Writing, Writing - Original Draft, Writing - Review & Editing, Visualization, Supervision, Project Administration, Funding Acquisition. **MH:** Software, Methodology, Validation, Writing - Review & Editing. **FAS:** Investigation, Data Curation, Writing - Review & Editing. **AU:** Investigation, Data Curation, Writing - Review & Editing. **ESK:** Methodology, Validation, Writing - Review & Editing.

Data availability

Data will be made available on request.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.160301>.

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