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ENVIRONMENTAL RESEARCH HEALTH

PAPER

Moving toward a more human-oriented analysis of urban heat: examining differences of heat exposure intensity at busy commuting locations

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Abstract

Examining urban thermal environments has become a critical area of research spanning epidemiology, urban planning, and ecology. While traditional metrics like air temperature (T_{air}) and satellite-derived surface temperature dominate urban heat studies, these measures often fail to reflect how people actually experience thermal exposure intensity. More human-oriented metrics, such as mean radiant temperature (MRT), and the wet bulb globe temperature (WBGT), better capture this lived experience, particularly at locations where people are likely to encounter outdoor heat, such as bus stops. Human demographics further complicate heat exposure, as access to cooling resources like trees and greenspaces can vary by neighborhood income. Our study addresses these complications by collecting thermal data across 60 commuting locations in Denver, Colorado in the summer. We evaluate (1) the extent to which more human-oriented metrics capture thermal exposure compared to T_{air} and LST, and (2) how heat exposure varies by neighborhood income levels. We observed that bus stops in low-income neighborhoods had an MRT increase 2.8 °C compared wealthier neighborhoods, and that income-driven differences in MRT and WBGT strongly depended on bus stop aspect. After accounting for solar orientation, differences in MRT increased to as much as 6.3 °C at north-facing stops. Our results suggest tree canopy shade explains some observed heat exposure patterns, with south facing bus stops seeing a MRT and WBGT decrease of 0.42 °C and 0.11 °C from a percent increase in tree canopy. Interestingly, depending on bus stop aspect, nearby buildings can increase MRT and WBGT (facing east), or decrease MRT and WBGT (facing south) If planners aim to address this issue, consideration of bus stops, and land covers configuration may help.

1. Introduction

Examining the spatial distribution of urban thermal environments is rapidly becoming a major research area spanning multiple fields of study, from urban climatology, epidemiology, urban planning, and vegetation ecology among others (Venter *et al* 2021, Basu *et al* 2024, McDonald *et al* 2024, Crawford *et al* 2025). In these fields, research narratives are often framed around how exposure to extreme thermal environments impacts the activities and well-being of humans in cities. Even when human health is not

a direct variable in the analysis, it often features in the overall narrative and summary conclusions. An individual's activity pattern has shown to be a significant factor in how individuals experience exposure to urban heat, therefore research could benefit by including variables explaining or accounting for that human experience (Heng and Chow 2019, Aghamohammadi *et al* 2021, Turner *et al* 2023). This shift in research perspective, from describing the urban thermal environment to understanding how humans experience the urban thermal environment, necessitates discussion of what analytical metrics of heat are best translated to a human experience. Metrics are best served focusing on *where* people are most likely to experience exposure to hazardous thermal environments, and *who* among a diverse urban population is more likely to be affected by urban heat exposure (Middel *et al* 2016, Lanza and Durand 2021, Wang *et al* 2023). Following Nazarian and Lee (2021), we distinguish human-oriented assessments that incorporate individualized factors (e.g. clothing, activity, physiology) from human-scale, receptor-oriented exposure assessments that prioritize measuring conditions where people are exposed (Nazarian and Lee 2021).

A possible first approach in reframing urban heat research to a more human context requires new ways to measure heat. An on-going debate exists over what is a suitable thermal metric for urban heat analysis (Nazarian *et al* 2022). Urban heat research has been dominated by two main metrics for decades: air temperature (T_{air}) and satellite-derived surface temperature (SD-LST). T_{air} has been used to examine urban heat dynamics for a century, being the focus of one of the first urban heat island (UHI) studies, and has been a common measure of heat ever since (Parry and Chandler 1966, Oke 1976). T_{air} studies have spatial and temporal limitations, as they require on-site sensors to record data and do not discern between sun-exposed or shade conditions (Shi *et al* 2021). Recent advances in statistical and mechanistic modeling have expanded the spatial extent of T_{air} analysis by interpolating T_{air} through its relationship with land cover and background temperature (Shandas *et al* 2019, Bilang *et al* 2022, Ibsen *et al* 2024). SD-LST is common in urban heat studies due to long-running public archives (Yang *et al* 2020), allowing for spatial analysis within and among cities. Contemporary research has found that SD-LST does not capture how people experience a thermal environment, especially during summer daytime hours where SD-LST reflect the heat of sun-exposed roofs and pavements, rather than the conditions within an urban canopy (Kelly Turner *et al* 2022, Li *et al* 2023, Naserikia *et al* 2024). However, a recent review found that approximately 50% of urban tree-cooling literature still used SD-LST as their primary urban thermal metric of study (Alonzo *et al* 2025).

More recently, research has highlighted the usefulness of more human-related heat metrics, as opposed to metrics measuring coarse LST or atmospheric conditions. These metrics are more attuned to how an individual physically experiences heat, from approximating the average thermal radiation received on a body by approximating the radiant environment experienced by a person (mean radiant temperature, MRT), to incorporating air temperature in the context of human activity and relative humidity (RH) (wet bulb globe temp, WBGT), to metrics tied directly to human perceptions (e.g. physiological equivalent temperature, PET) (Matzarakis *et al* 1999, Budd 2008, Vanos *et al* 2021). Though these metrics represent a small portion of urban heat studies, they represent a shift to a more human-oriented and exposure-focused scale of analysis that furthers an understanding of what determines a more thermally pleasant environment.

Along with a shift to more human-oriented metrics of heat, urban heat research has begun to focus on locations where people are more likely to be exposed to extreme thermal environments. Urban heat research has historically been focused on exploring the UHI phenomena, or the difference between air and surface temperatures in urban versus rural areas (Parry and Chandler 1966, Arnfield 2003). Recently, research has examined dynamics of within-city heat, either across the entire urban extent, or at specific scales of analysis, such as parks or greenspaces (Feyisa *et al* 2014, Hu *et al* 2021, Smith *et al* 2023). These within-urban heat comparisons are often paired with population demographics to gain an understanding of which population groups are spatially linked to different thermal conditions (Dialesandro *et al* 2021).

In addition, these studies have focused on who has more access to shaded neighborhoods (Locke *et al* 2021), or areas like bus stops, athletic fields, and busy walking thoroughfares (Guyer *et al* 2021, Lanza and Durand 2021, Basu *et al* 2024). When a study is directly linked to a location where people spend time, we can better understand interactions between people and heat, and then potentially better relate that experience to health and activity (Dzyuban *et al* 2021).

When urban heat studies attune heat metrics and spatial scale to human activity patterns often it finds the human experience of heat is not uniform (Heng and Chow 2019). Research has identified past and present drivers of heat exposure vary across demographic and socioeconomic variables (Tuholske *et al* 2021). In multiple cities, researchers have found that the legacy of racial and economic segregation has contributed to hotter neighborhoods, often through reduced tree cover and greenspace, due to a lack of investment in land cover that reduces heat, such as trees or greenspaces (Hoffman *et al* 2020,

Yeager *et al* 2023, McDonald *et al* 2024). Within cities, the spatial geography of infrastructure is also not equal, with more affluent areas being dominated by residential spaces and less affluent areas containing more commercial and industrial zones, which leads to disparities in heat exposure (Hart and Sailor 2009, Ming *et al* 2024). Moreover, lower-income and working-class populations are more dependent on public transit, which requires them to spend more time outside, exposed to potentially harmful environments (Daniels and Mulley 2013).

Some recent studies have focused more directly on the individualized human experience of thermal conditions. These works have included direct surveys of individuals thermal perceptions (Steinharter *et al* 2025), using personalized data such as clothing and demographics in calculating a focused human-centric thermal metric like PET (Vanos *et al* 2020), and employing simulations which can model different individualized experiences based on parameterized physiological conditions (Liu *et al* 2024). These studies are notable for explaining direct factors on individuals thermal comfort, however they are difficult to generalize outside of their boundary conditions across larger spatial extents. Either due to the specific data collected on individuals, or due to the computational power needed to run physical models across city-wide areas consisting of complex land cover heterogeneity.

With all these factors in mind, we aim to resolve issues of how human-centric heat metrics, spatial urban geography, and socioeconomics, interact, in the context of urban planning decisions, such as the land cover arrangements surrounding bus stops of differing spatial aspects. With the understanding the purely human-centric metrics that take into account human morphology, activity levels, and clothing are difficult to generalize, our goal is to more urban heat analysis through a more human-oriented lens, while still applying the results spatially for multiple scenarios. We collect approximated MRT to represent the radiant energy load received by a human, providing a spatially explicit measure of thermal intensity; and WBGT to represent how thermal exposure is influenced by local RH, at commuting locations across an entire city, we can test the hypotheses: (1) human-oriented heat metrics are more attuned to a commuter experience than common metrics of SD-LST and T_{air} , as a human-oriented metric is able to incorporate multiple facets of a thermal environment, (2) exposure to extreme heat is highest in commuting locations within lower-income neighborhoods due to the lack of trees and shading. In testing these hypotheses our goals are to provide a greater understanding of the urban thermal environment at a human scale, both through how an individual experiences radiative heat exposure (MRT), and how they experience heat intensity in the presence of humidity (WBGT).

Through that understanding, we aim to provide applicable results to urban planners or land managers who desire to moderate that thermal environment to enhance outdoor comfort. To this end, using a combination of *in-situ* microclimate data, SD-LST, high-resolution land cover data, and regional climate data, we create a statistical model to predict thermal exposure intensity at commuting locations across an urban environment.

While the concept of ‘heat exposure’ encompasses intensity, duration, and frequency (Kuras *et al* 2017); our analysis is specifically focused on the intensity parameter. We focus on exposure intensity as it most directly captures the thermal experience at a given place and time, such as when waiting at bus stop, and thus can be spatially modeled. Assessing duration and frequency (which would require individual mobility or behavioral models) fall beyond the scope of this study.

2. Methods

2.1. Study locations

To focus on urban heat exposure at the human scale, we selected 60 bus stop locations across Denver, Colorado, USA, to collect heat data. Denver, a semi-arid city situated at approximately 1600 m above sea level, had previously been recognized as a location with significant differences in heat exposure between economic groups (Dialesandro *et al* 2021).

We based our selection of specific bus stops on three factors. First, we identified a gradient of land cover, particularly tree canopy, surrounding each bus stop. We accomplished this step by using a high-resolution (1 m²) land cover dataset provided by the Denver Regional Council of Governments (DRCOG Regional Data Catalog 2018). We applied a 15 m buffer around the centroid of all bus stops within the Denver Regional Transportation District (RTD) service area and extracted the land cover proportions within this buffer using the Tabulate Area tool in ArcGIS Pro (ESRI). This buffer size is to represent not just the full sidewalk area surrounding the bus stop, but also include the nearest surrounding land cover types which commuters could interact with (i.e. standing in available tree or building-created shade behind the bus stop), as well as capturing a section of the roadway which could influence the thermal environment.

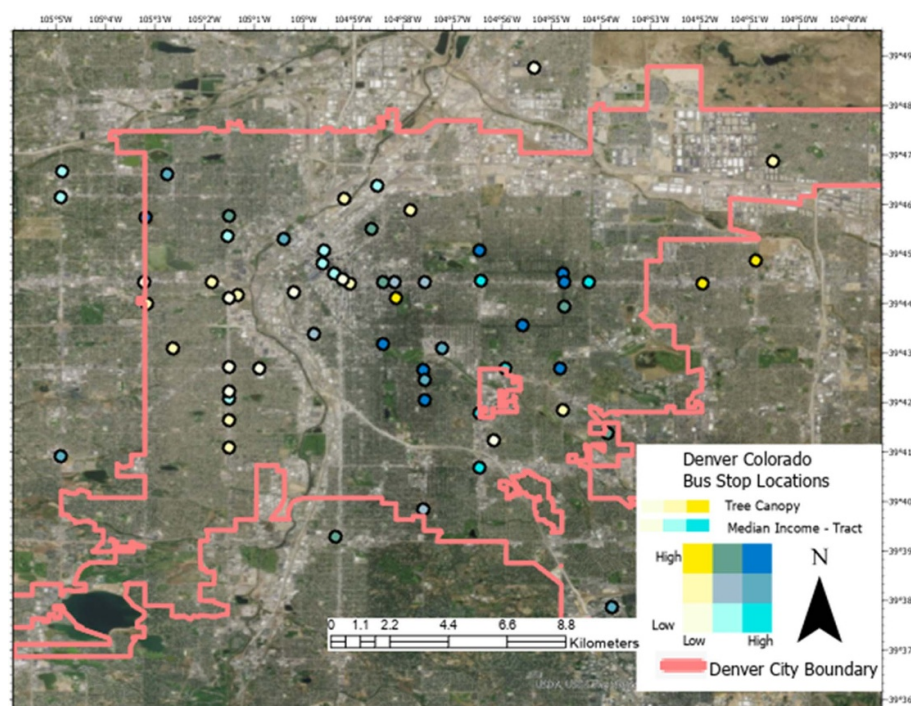


Figure 1. Location of bus stop locations used in the study within the Denver Colorado metropolitan area. Bus stops are colored based on their proportion of surrounding tree canopy and the surrounding census tract-scale median household income. Selected bus stops were also chosen to represent areas of high ridership. Map services and data available from U.S. Geological Survey, National Geospatial Program.

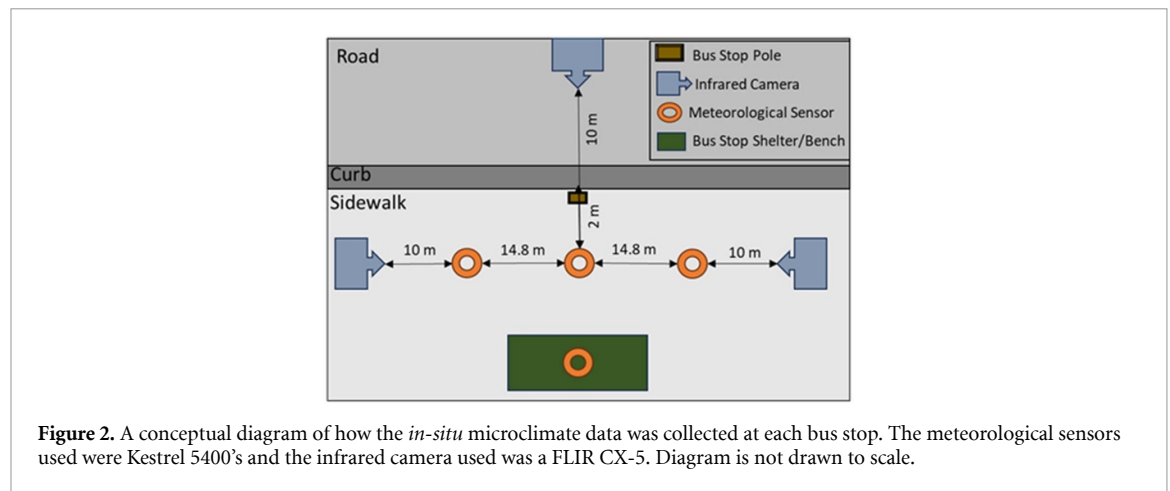
Next, we associated each bus stop location with the median household income of the surrounding census tract, based on data from the U.S. Census Bureau's American Community Survey 5 year Estimates Data (U.S. Census Bureau's American Community Survey Office 2020). While this does not give an exact description of income status of each active commuter at the location, it can be used to estimate the general household income level of homes within a walking distance to the bus stop. To ensure our measurements aligned with human exposure at those sites, we excluded any bus stops with low average daily ridership, using ridership data provided in partnership with the RTD. Using these three criteria, we identified 60 locations that captured gradients of high/low surrounding tree canopy and high/low neighborhood household income (figure 1). For analyzing land cover influences on thermal environments, we associated each bus stop with the fraction of land cover composed of trees, grass, impervious surfaces, and buildings as provided by DRCOG. Additionally, we assigned each bus stop a cardinal direction to account for the sun exposure of which direction the bus stop is facing.

2.2. Measuring the thermal environment

We used Kestrel 5400 Globe Thermometers (Kestrel Instruments) to collect the following thermal environmental data: air temperature (T_{air}), RH, dry bulb globe temperature (DBGT), WBGT, and wind speed (ws). We placed Kestrel sensors on tripods approximately 1.1 m above the ground. At each study location, we positioned three sensors (k1, k2, k3) in a line, spaced 4.8 m apart. We standardized the center sensor to be exactly 2 m away from the curb where the pole with the bus stop signage was located. If a bus stop featured a shelter or bench, we placed a fourth sensor (k4) within or on the structure (figure 2). Bus stop locations ranged in elevation by 133 m.

Kestrels were calibrated and tested for individual bias prior to deployment (no bias was detected). While Kestrel anemometers have been observed to occasionally product erratic readings at very low wss, previous research have shown these potential unstable readings have non-significant influence on heat exposure indices such as WBGT (Carter *et al* 2020). Moreover, in our dataset, only 8.4% of measurements (92 out of 1086) fell below the wind-detection limit. Of those, approximately half were recoded within bus shelters, where shading and reduced radiant load is more likely to dominate thermal exposure intensity.

To capture high-resolution surface temperature data, we used a FLIR CX-5 handheld thermal camera. We took thermal infrared images 10 m away from sensors k1–k3 and calculated the mean surface temperature beneath each sensor to directly relate surface temperature to the sensor read-outs (figure 2). We



then averaged the FLIR values for all sensors during every visit to calculate a mean surface temperature for the bus stop (LST_{FLIR}). We also calculated the standard deviation of the FLIR values to account for variability in shading at each location ($LST_{FLIR-SD}$). For example, should one sensor location be shaded on one side of the waiting area while another sensor is in direct sun, there will be a higher $LST_{FLIR-SD}$ for that location at that time.

We accounted for different commuting times by visiting each study location during morning hours (7:30–10:00) and afternoon hours (14:00–18:00). Bus stops were grouped into 9 routes that had efficient travel time between 6–7 sites in order to visit all route locations within the morning and afternoon windows. The daily data collection plan was determined by a random selection of the 9 routes to be sampled, so two field teams sampled two routes, collecting both morning and afternoon data for both, ensuring all morning data for a site could be paired with afternoon data of that same day. We revisited each site a minimum of three times during both morning and afternoon periods. The study took place between 8 July 2023, and 11 August 2023. By the end of the sampling period, our research team had collected 1353 microclimate measurements across 350 visits, though 10 visits were canceled due to inclement weather or encounters with aggressive individuals at the bus stops. After being deployed on the sidewalk or shelter, Kestrels were set up to acclimate for ten minutes prior to recording. Sensors recorded for two minutes, with their measurements averaged.

2.2.1. Calculating thermal comfort metrics

MRT represents the average thermal energy received by a human body, encompassing all shortwave radiation—including direct sunlight (unshaded), diffuse sunlight (filtered through clouds or haze), and reflected sunlight (from surrounding surfaces). MRT also includes longwave radiation, such as atmospheric thermal energy (from the sky) and emitted radiation (from surrounding surfaces) (Kántor and Unger 2011). Traditionally measured using a large black globe to capture all radiation types, recent advancements have allowed us to estimate MRT from globe temperature using data from the Kestrel 5400. This method combines DBGT, T_{air} , and WS to estimate MRT as described by Ouyang *et al*, and has lower error probability when used in open spaces when compared with the ISO equation (equation (1)) (Ouyang *et al* 2022),

$$MRT (^{\circ}C) = \left((DBGT + 273.15)^4 + \left(\frac{0.678 * 10^8 * ws^{0.019}}{0.95 * 150^{0.4}} \right) * (DBGT - T_{air}) \right)^{0.25} - 273.15. \quad (1)$$

While MRT is a radiative metric, this equation uses air temperature and ws to estimate point-source MRT from DBGT, rather than directly measuring multiple angles of radiative fluxes (Middel and Krayenhoff 2019). We removed any outliers that were three times or more the absolute deviation around the median of recorded DBGT, T_{air} , ws, or RH (Leys *et al* 2013).

WBGT was calculated within the Kestrel sensors. WBGT integrates air temperature, humidity, ws, and radiant heat to approximate the physiological stress associated with outdoor heat exposure. We use WBGT to describe how the thermal environment is perceived in relation to the body's ability to dissipate heat through sweating. Because humidity limits evaporative cooling, WBGT effectively captures how local moisture conditions moderate the body's ability to cool itself. Under many guidelines, WBGT values exceeding 23 °C are considered a threshold at which restrictions on strenuous outdoor activity are recommended (Brimicombe *et al* 2023).

2.3. Statistical analysis

2.3.1. MRT and WBGT as urban heat metrics

We aimed to evaluate how effectively MRT and WBGT function as metrics of thermal exposure. First, we assessed how MRT related to metrics of the surface thermal environment, with SD-LST representing the commonly used coarse-scale (30 m) urban heat metric and LST_{FLIR} representing high-resolution thermal data (<1 m). We derived SD-LST from the mean daytime value from cloud-free Landsat-derived surface temperature scenes available during the summertime study period, provided by 30 m downscaled Analysis Ready Data created by the U.S. Geological Survey (Dwyer *et al* 2018). We derived MRT, WBGT, and LST_{FLIR} values from the Kestrel and FLIR data at each sensor location. We calculated SD-LST as the mean of all available SD-LST data collected during the study period. This was done to provide a general value of local SD-LST at each commuting location. We aggregated SD-LST data to the 15 m buffer surrounding each selected bus stop using the Zonal Statistics tool in ArcGIS Pro. We analyzed each of these univariate relationships using linear regression for morning and afternoon conditions, using the adjusted R^2 value to determine the strength of each relationship.

2.3.2. Assessing differences in urban heat exposure

To relate heat exposure to human activity patterns, we aggregated MRT and WBGT values at bus stops within the economic class of the surrounding census tract. We determined economic class using categories developed by the Pew Research Center: ‘Middle’ income neighborhoods had tract-level median household incomes between 67% and 200% of the median household income for the Denver metropolitan region and year of analysis, while ‘Low’ and ‘High’ income neighborhoods fell below and above these thresholds, respectively (Fry and Taylor 2012). We compared the mean exposure intensity across the three income brackets using a one-way ANOVA and identified differences between groups through Tukey’s post-hoc analysis, with significance set at an alpha level of 0.05. To examine the effect of bus stop directional aspect on heat exposure, we repeated the ANOVA tests for bus stops grouped by their facing direction.

To measure how land cover affected thermal exposure, we calculated a thermal anomaly, defined as the difference between the observed thermal exposure and the mean thermal exposure for the specific bus stop direction aspect. To identify land cover drivers of direction specific anomalies, we performed a spatial mixed regression using four land cover fractions as fixed effects, while we used an exponential correlation structure applied to the longitude and latitude of each sampled bus stop. The full model was fit using maximum likelihood estimations. Significance of the coefficients was determined by assuming a normal distribution then calculating the Wald Z-statistic (the ratio of a fixed-effect estimate to its standard error), and then converting those statistics to p -values (Zuur *et al* 2009). We also calculated the 95% confidence intervals to assess the robustness of the land cover fixed-effect estimates. Analysis was conducted for morning and afternoon commutes.

2.3.3. Modeling and predicting MRT across multiple commuter locations

Next, we evaluated the statistical strength of how a multivariate combination of surface thermal metrics, land cover data, and regional climate influence MRT. We focused our spatial predictive model on MRT with the objective to develop a generalizable framework that can be applied using regional climate and land cover, whereas WBGT depends strongly on the local humidity. Relationships between land cover types and the thermal environment can be non-linear (Locke *et al* 2024), so we used two random forest models with MRT as the response variable. In one model, predictor variables included SD-LST, surrounding land cover fractions (tree canopy, grass, impervious surfaces, and building fractions within the 15 m buffer), and regional climate (air temperature, RH, ws, and precipitation). In the second model, we replaced SD-LST with LST_{FLIR} and $LST_{FLIR-SD}$ to determine how well the higher-resolution surface temperature data improved the model. We determined regional climate variables as the mean values recorded at the hour closest to the *in-situ* sampling, derived from the three surrounding airports: Denver International Airport, Buckley Space Force Base, and Centennial Airport. We optimized the random forest model by tuning the number of variables used for each node, resulting in using an n of 4. We trained the model on 70% of the dataset and tested its performance on the remaining 30%. Model performance was evaluated using the adjusted R^2 value from the linear regression between observed and predicted MRT values in the test dataset. We assessed variable importance based on the relative increase in mean squared error, with higher importance assigned to variables that caused greater declines in model accuracy when excluded. Random forest models were built for morning and afternoon commuting hours.

To build a statistically sound model to predict MRT at locations beyond the sampled sites and using only publicly available data sets, we focused our studies on locations that were geographically similar to

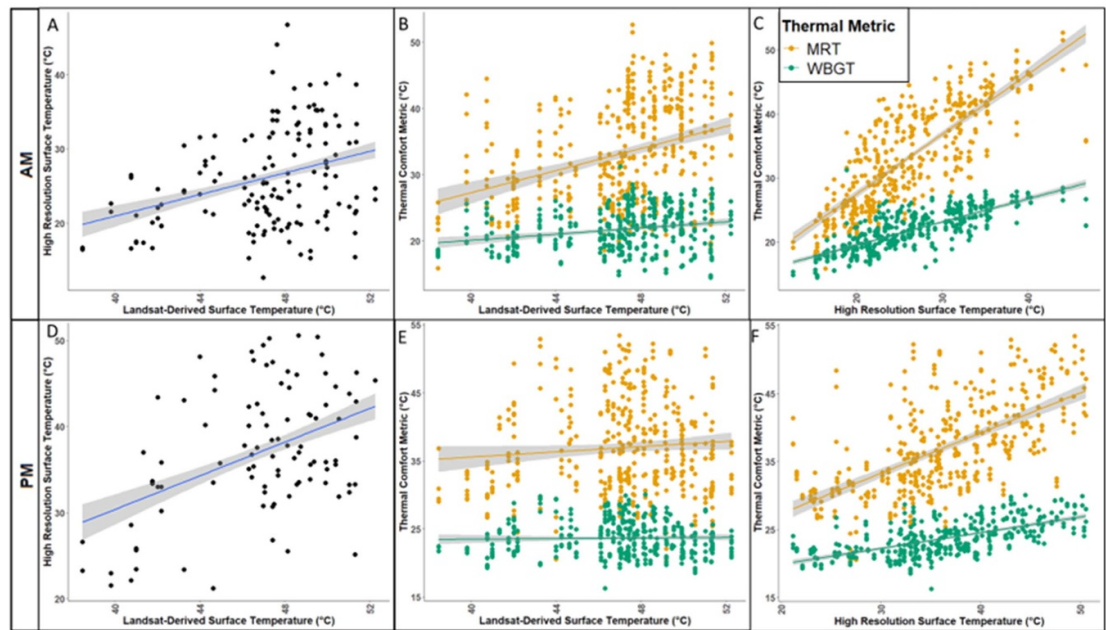


Figure 3. Comparisons between three different metrics of the urban thermal environment during different times of the day. The relationship of Landsat-derived surface temperature and high-resolution surface temperature (from a FLIR camera), during the morning (A) and afternoon (D). The association of Landsat-derived surface temperature on mean radiant temperature, during the morning (B) and afternoon (E). The association of high-resolution surface temperature (from a FLIR camera) mean radiant temperature, during the morning (C) and afternoon (F). Shading surrounding linear regression lines indicates the standard error.

our study locations. As many bus stops are located very close to each other, often on adjacent streets and traffic-flow directions, we included all bus stops within 400 m of each sampled location. The choice of this distance is based on prior studies that determine an average individual will walk approximately 400 m from their home to reach a bus stop (El-Geneidy *et al* 2014). This way we could include all bus stops that were likely to be visited within each study area. We aimed to make a useful model with only publicly available data, thus we did not want to use any of our sensors to predict MRT at this scale. With that in mind, we first made a predictive model of LST_{FLIR} using a random forest algorithm, with regional climate, land cover fractions, and SD-LST as predictors. This process results in a set of corrected SD-LST values which can then be applied as a predictor for MRT. All statistical analysis was conducted in R version 4.4.0 (RStudio Team 2021), using the following packages for random forest analysis (randomForest, (Breiman 2001)), and for the spatial mixed modeling (spaMM, (Rousset and Ferdy 2014)).

3. Results

3.1. Drivers of the heat exposure at the human-scale

Across the bus stops we visited; we observed large differences when comparing common urban thermal metrics (figure 3). To compare the aggregated SD-LST value to LST_{FLIR} , we aggregated all collected LST_{FLIR} data to daily morning and afternoon means for each visit, creating a generalized bus-stop LST_{FLIR} value. Even though there is a temporal disconnect between the collections of SD-LST and LST_{FLIR} , we discovered that SD-LST was a significant predictor of LST_{FLIR} during mornings and afternoons, though there was not a strong model fit (morning: $p < 0.001$, $Adj. R^2 = 0.12$; afternoon: $p < 0.001$, $Adj. R^2 = 0.15$, (figure 3(A) & D)). SD-LST was only a significant predictor of MRT and WBGT during morning hours (MRT: $p < 0.001$, $Adj. R^2 = 0.11$; WBGT: $p < 0.001$, $Adj. R^2 = 0.01$), and was non-significant during the afternoon (figures 3(B) and (E)), which is somewhat expected due to SD-LST data being obtained in early afternoon flyovers. However, LST_{FLIR} was a much better predictor of MRT and WBGT than SD-LST, with stronger associations during the morning and afternoon (morning: MRT: $p < 0.001$, $Adj. R^2 = 0.64$ —WBGT: $p < 0.001$, $Adj. R^2 = 0.59$; afternoon: MRT: $p < 0.001$, $Adj. R^2 = 0.38$, WBGT: $p < 0.001$, $Adj. R^2 = 0.42$, (figures 3(C) and (F))).

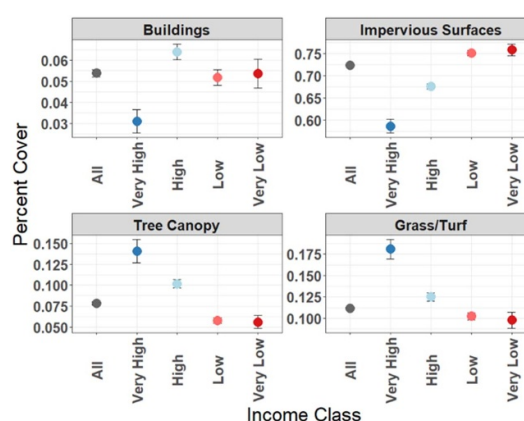


Figure 4. The percent cover of urban land covers within a 15 m buffer of all Denver bus stops, separated by mean income of census tract. Income bins are determined by the income percentile of tract; very low $\leq 5\%$, $5\% < \text{low} < 25\%$, $25\% < \text{high} < 75\%$, $75\% < \text{high} < 95\%$, $\text{high} \geq 95\%$. Points represent means and error bars represent standard error. Significance determined by ANOVA. Differences between means represented by differing letters determined by Tukey's post hoc test, items with the same letter are not significantly different.

3.2. Patterns of commuter heat exposure across income groups

The land cover surrounding bus stops varied by neighborhood median income (figure 4). Bus stops in higher-income neighborhoods had significantly greater percent cover of tree canopy and grass, and significantly less impervious surfaces and buildings when compared to lower-income neighborhoods, except for the percent cover of buildings, which was highest in high income neighborhoods.

We found a significant difference in thermal exposure intensity metrics on bus stop sidewalks within neighborhoods of varying income classes (figure 5). During the morning hours, bus stops in high-income neighborhoods were approximately 4°C and 1.2°C cooler than bus stops in low- and middle-income neighborhoods, respectively. We found a slightly different pattern during the afternoon, where the low-income neighborhood was 2.7°C and 2°C hotter than high- and middle-income neighborhoods, respectively. We found no significant differences in heat exposure when comparing MRT in bus stop shelters across different neighborhoods. While we did find significant MRT differences between bus stop sidewalks and shelters, we found no difference in T_{air} between sidewalk and shelter (supplemental figure 1).

When we grouped data into bus stops that shared a specific aspect (figures 6 (A), (B) and 7(A), (B)), we found no significant association between income class and MRT exposure within bus stop shelters (figures 6 (A) and (B)). Though, we did observe a significantly higher WBGT temperatures in south facing shelters during the afternoon (figure 7(B)). For sidewalk exposure, we found that associations between income and heat exposure were also determined by the aspect of the bus stop. During morning and afternoon hours, the sidewalks of west-facing bus stops did not differ across income classes. However, east- and south-facing low-income commuting locations were significantly warmer than high-income locations at both times of the day. Unsurprisingly, north-facing low-income locations were significantly cooler in the morning but significantly warmer in the afternoon. Differences between high- and middle-income, and low- and middle-income bus stops varied depending on the time of day.

The effects of land cover fraction on the thermal anomaly varied depending on the time of day and the bus stop aspect (figure 8). Building fractions at east-facing bus stops were significantly associated with a heat increase, with every percent increase in building cover resulting in a mean 0.68°C and 1.1°C increase in the MRT anomaly during morning and afternoon hours, respectively. Similarly, each percent increase in building cover resulted in a 0.23°C and a 0.21°C WBGT anomaly increase in the morning and afternoon. No other land cover exhibited a significant influence on the thermal anomaly during the day. However, in the afternoon at east- and south-facing bus stops, we found that certain land covers significantly lowered the thermal anomaly. Tree canopy reduced MRT anomalies in both bus stop aspects (WBGT was only significantly lowered by trees in the south facing aspect). Buildings lowered south and east-facing MRT anomalies (WBGT was only significant lowered by buildings in the south facing aspect). Impervious surfaces lowered the east-facing MRT and WBGT anomalies.

3.3. Modeling MRT across multiple commuting locations

As we found no significant impact of income on MRT within bus stop shelters, we focused our predictive MRT models to only the sidewalk waiting areas of each bus stop. Our random forest model

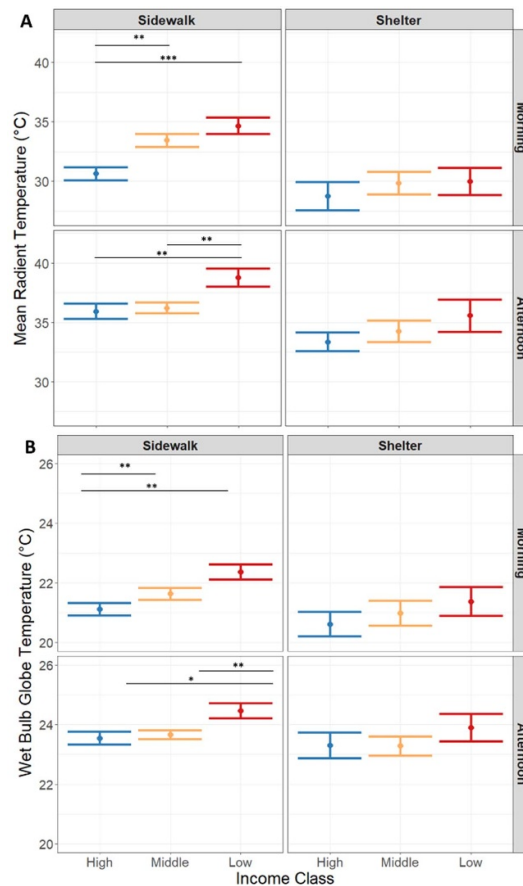


Figure 5. Differences between (A) mean radiant temperature and (B) wet bulb globe temperature exposure intensity at sampled bus stops in neighborhoods of varying income class. Analysis was conducted both on the sidewalk and within bus stop shelters, and during morning and afternoon hours. Points represent the mean MRT value by income class and error bars represent standard error. Top bars and asterisks across income groups indicate a significant difference between groups, tested with ANOVA and a post-hoc Tukey HSD test ($0.01 < p < 0.05 = *$; $0.001 < p < 0.01 = **$; $p < 0.001 = ***$).

which described MRT during morning hours explained 74% of variation in the test data. LST_{FLIR} and $LST_{FLIR-SD}$ combined provided 37.5% of total importance within the model. The surrounding land cover contributed 36.3% of model importance, with tree canopy being the most important land cover variable. Regional weather patterns contributed 26.1% (figure 9). During the afternoon, the random forest model explained 80.8% of the total variation in the test data. The combination of LST_{FLIR} and $LST_{FLIR-SD}$ combined to provide 30.9% on model importance, and land cover and regional weather contributed 36.9% and 32.0% respectively, with impervious surfaces being the most important land cover variable.

The corrected SD-LST model was significantly related to the LST_{FLIR} data ($p < 0.001$, adj. $R^2 = 0.95$) (supplemental figure 2). When using the corrected SD-LST data to predict MRT, our results showed a strong significant correlation to our observed *in-situ* MRT data during morning and afternoon (figure 10) (**morning:** $p < 0.001$, adj. $R^2 = 0.82$; **afternoon:** $p < 0.001$, adj. $R^2 = 0.91$).

4. Discussion

Overall, our study was able to identify key drivers of both how commuter exposure to extreme heat differed by neighborhood income, but also how that difference is amplified at bus stops of specific directional aspects. Our results support our first hypothesis that MRT and WBGT provide a more exposure-relevant characterization of thermal exposure intensity than SD-LST or T_{air} . This better characterization arises from their ability to integrate radiative loading across different land cover types (MRT) and humidity-dependent heat stress (WBGT), both components that are missed by metrics solely based on air or SD-LSTs. Figure 3(D) showed evidence of this, as SD-LST was poor in approximating human-scale thermal environments during afternoon hours, while MRT, WBGT, and LST_{FLIR} (figure 3(F)) more effectively modeled this relationship. The limitations of SD-LST explained these results. SD-LST only captured canopy temperatures and rarely collected data from shaded surfaces. Additionally, the SD-LST

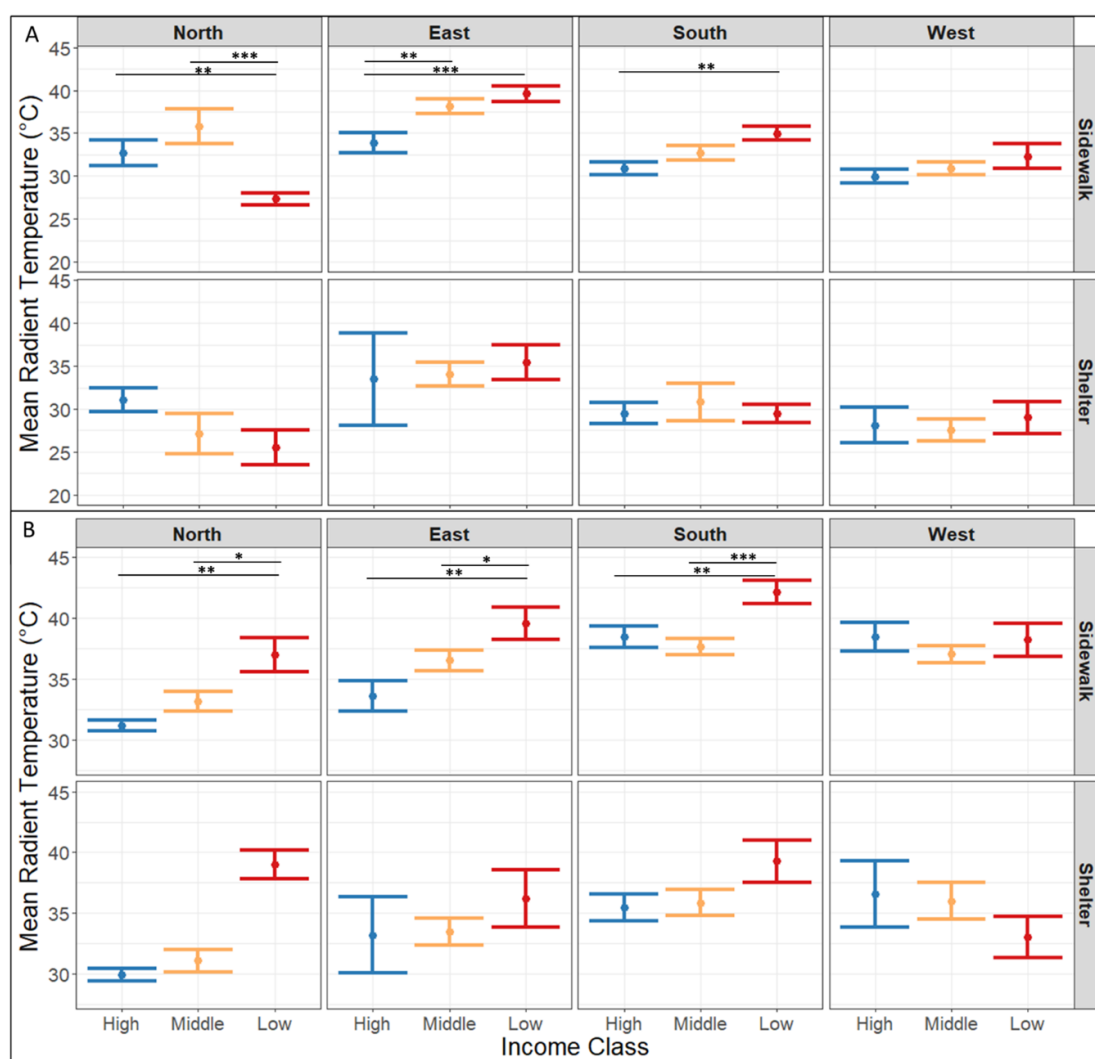
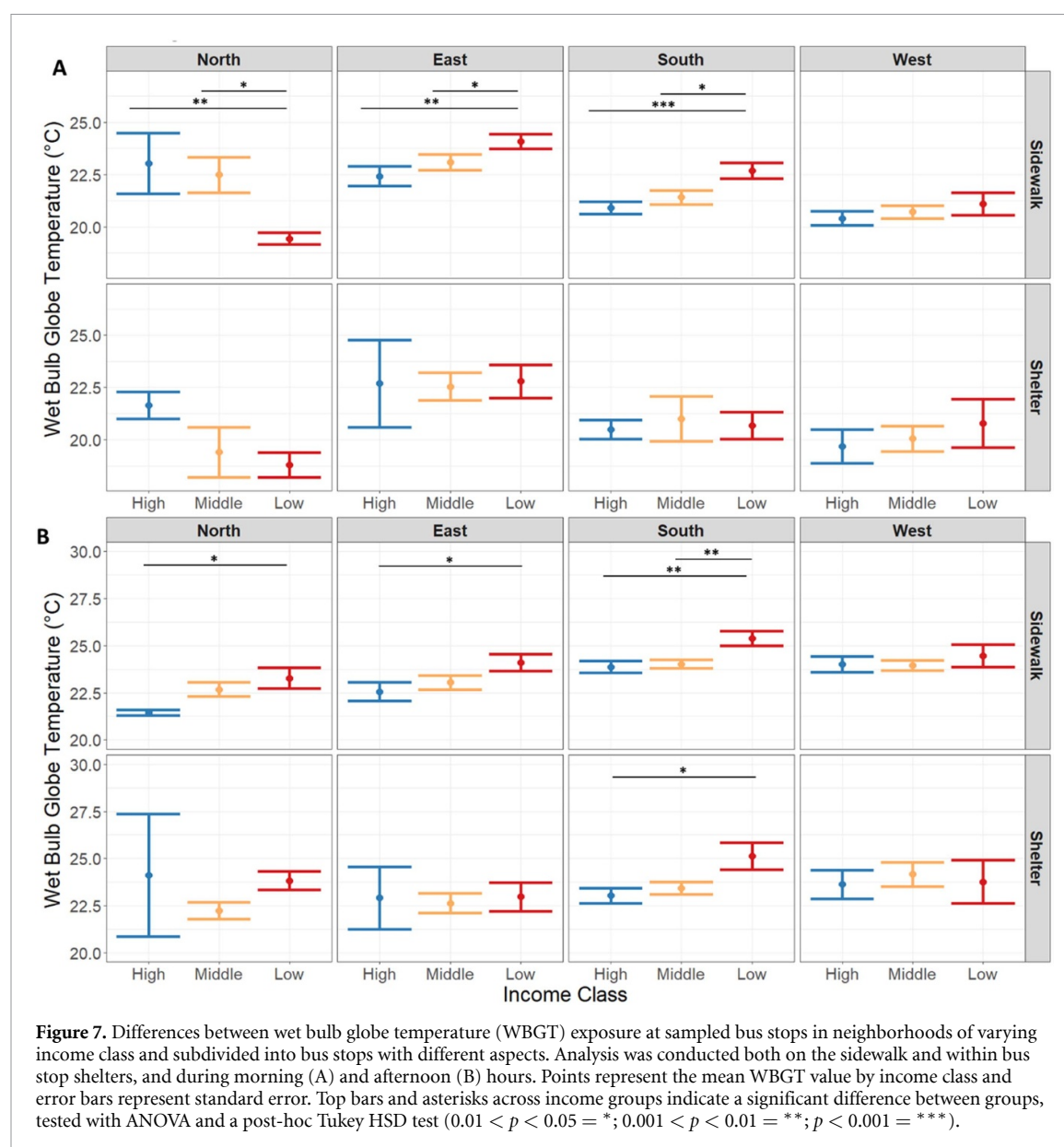


Figure 6. Differences between mean radiant temperature exposure at sampled bus stops in neighborhoods of varying income class, and subdivided into bus stops with different aspects. Analysis was conducted both on the sidewalk and within bus stop shelters, and during morning (A) and afternoon (B) hours. Points represent the mean MRT value by income class and error bars represent standard error. Top bars and asterisks across income groups indicate a significant difference between groups, tested with ANOVA and a post-hoc Tukey HSD test ($0.01 < p < 0.05 = *$; $0.001 < p < 0.01 = **$; $p < 0.001 = ***$).

satellite used in this study (Landsat) conducted flyovers near solar noon, well before the peak heat of the day. As temperatures rose, the differences between T_{air} and LST increased (Crum and Jenerette 2017). More human-oriented and exposure-relevant thermal measurements captured the complexity of surface thermal radiation (recorded as LST_{FLIR}) and changes in air temperature more effectively than SD-LST.

Figure 5 effectively highlights the importance of shade when analyzing the distribution of heat exposure at a human scale. Our results showed that bus stops in lower-income neighborhoods experienced higher heat exposure compared to those in wealthier neighborhoods. However, this significant difference disappeared when bus stop shelters were present. The shade provided by the shelters created areas shielded from shortwave thermal radiation, a major contributor to heat exposure and risk (Lin *et al* 2010, Lam *et al* 2023).

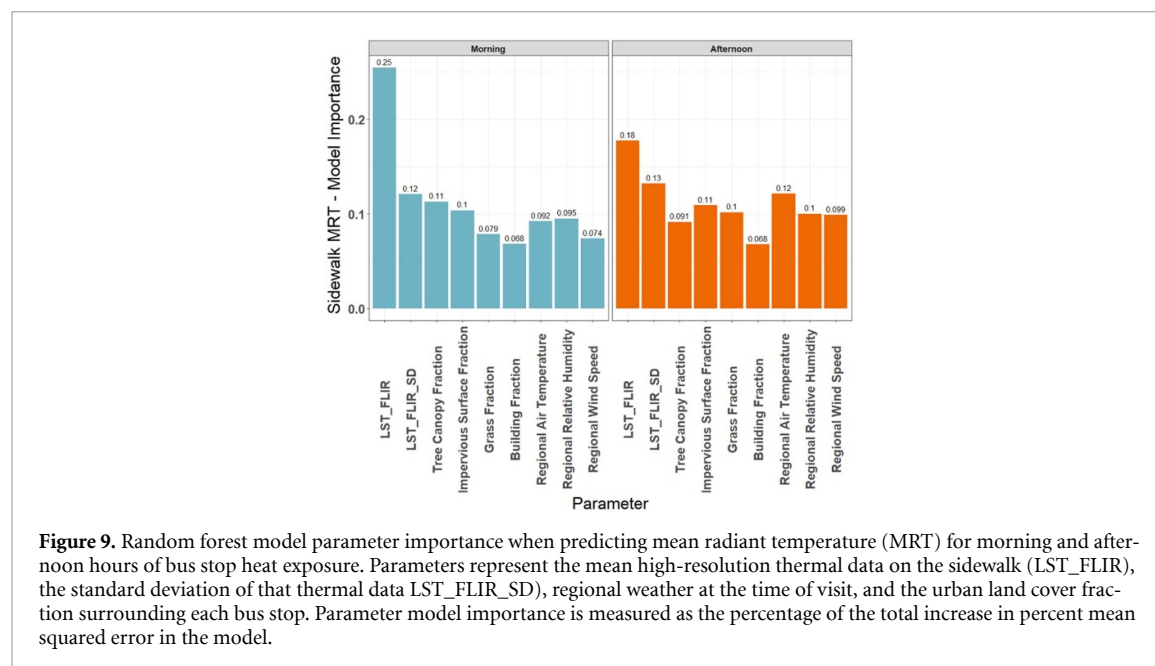
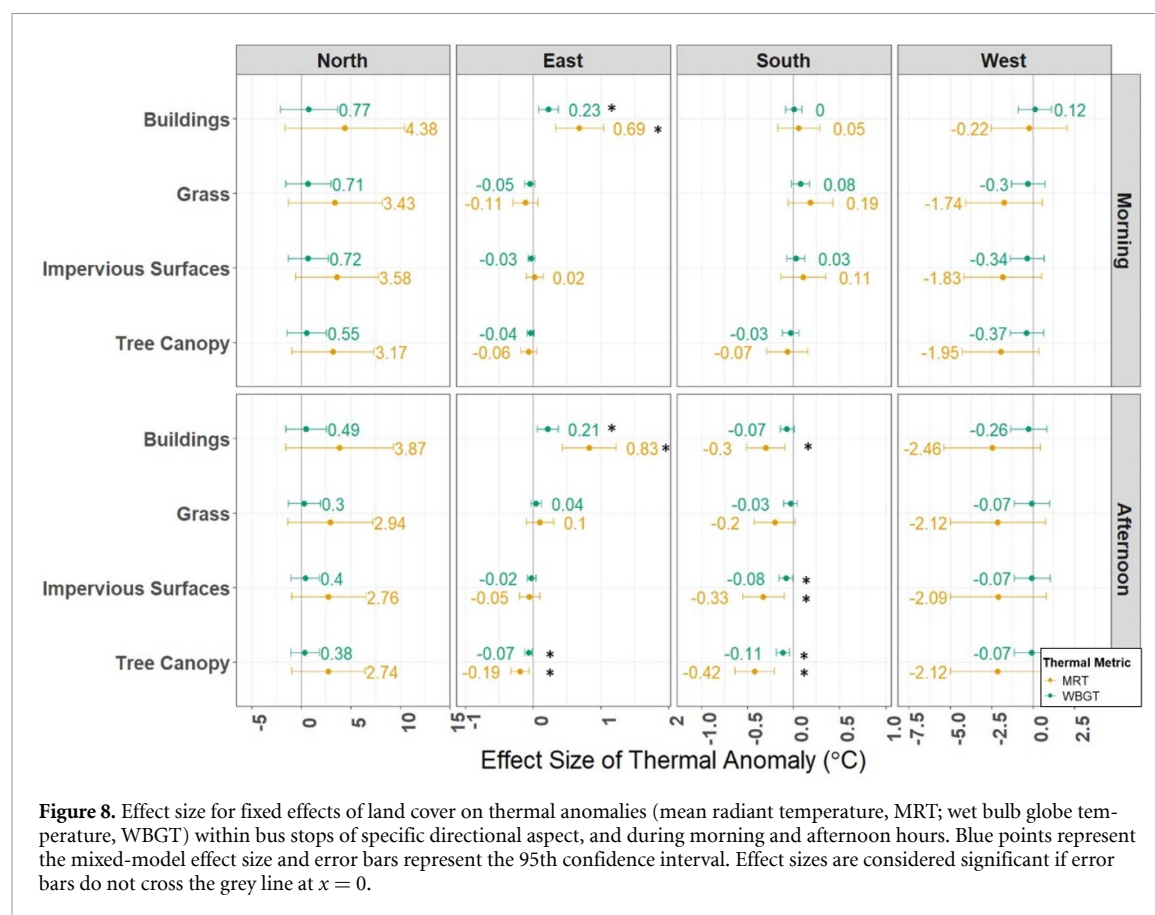
Notably, the cooling benefit of shelters did not translate to being noticeable by air temperature measurements. T_{air} showed no significant difference between the sidewalk and sheltered waiting area, whereas MRT and WBGT decreased substantially (supplemental figure 1). This divergence is important to note, as at commuter locations, exposure intensity is driven primarily by radiative load (sun–shade contrasts) rather than local air temperature, meaning shade interventions can reduce exposure even when T_{air} remains unchanged. Accordingly, analyses that rely on T_{air} alone may underestimate both the magnitude of commuter heat-exposure inequities and the effectiveness of shade-focused mitigation. Adding shade



structures to bus stops, particularly those with sparse tree canopy in the afternoon could reduce commuter heat exposure and the associated potential negative health and economic outcomes. Were only T_{air} -based assessments used to analyze heat exposure, practitioners could fail to detect a very consequential feature of the commuting environment which could have strong effects in predicting heat exposure health outcomes.

However, as we see in figures 6 and 7, simply identifying the hottest bus stops is not enough to know where the biggest difference in heat risk across income groups is found. The direction a bus stop faces affects the incoming solar radiation. We found no significant differences in thermal exposure intensity across income classes at west-facing bus stops. But this is not to say west-facing bus stops are cooler than the rest. Our interpretation of this result is a demonstration that the configuration of shade matters greatly in reducing heat exposure (Abram *et al* 2022). A west-facing bus stop receives primarily direct afternoon sun, which makes shading sidewalks very difficult, as a shade-giving tree would have to be positioned in front of the sidewalk, which is primarily a street area used for vehicular transit. Simply put, you cannot plant a tree in the middle of the road, and tree canopies which extend over a road are at higher risk of damage and obstructing vehicular traffic (Mullaney *et al* 2015, Roman *et al* 2020). When a bus stop is positioned where morning or afternoon sunlight comes in from a direction not perpendicular to the street direction, there are more opportunities for shade to be cast along the sidewalk.

Differences in heat exposure occur when bus stops in lower-income neighborhoods have generally less trees (Locke *et al* 2021), which we observed in Denver (figure 4). When bus stops face south, trees



can provide opportunistic shade which reduces MRT and WBGT exposure, which is different to the north aspects, where shade is more equally distributed over the bus stop (figure 7). As we find more trees in wealthier neighborhoods, we can interpret shade-provisioning, and the resultant heat reduction, as a factor of economic opportunity adding evidence to our second hypothesis that commuting locations in lower income neighborhoods have greater exposure to extreme heat. This result also highlights the trade-offs that come with urban tree planting (Roman *et al* 2020). Interestingly, we also see the opposite as north facing bus stops in low income neighborhoods are cooler in the morning (figure 3(A)). Here may be a unique example of in places with a lot of shade and little radiation, the insulating aspect of

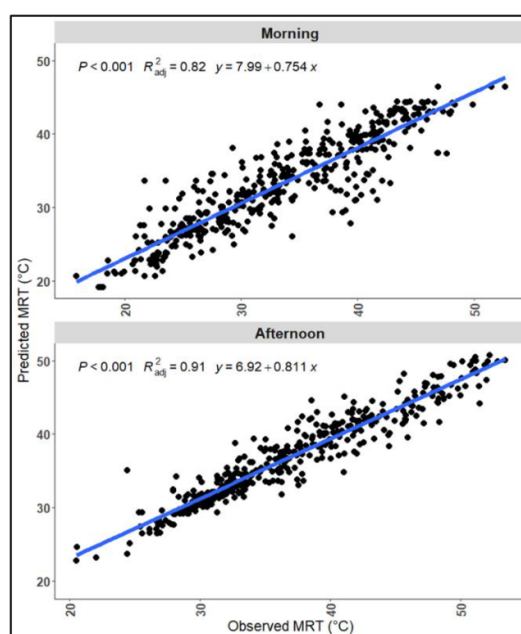


Figure 10. Comparison of predicted mean radiant temperature (MRT) with our *in-situ* measured MRT values at bus stops during morning and afternoon hours. Predicted values are created through a random forest model using corrected surface temperature values, land cover, bus stop aspect, and regional weather patterns.

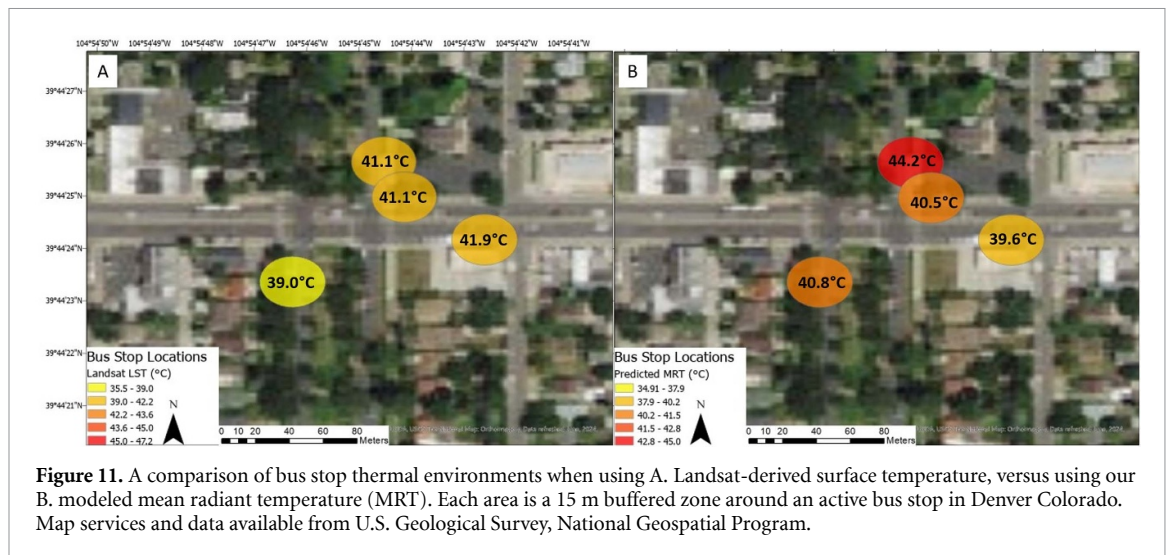
tree canopy may increase the warmth of the wealthier neighborhood bus stops (Wujeska-Klaue and Pfautsch 2020). While in bus stops with less canopy cover, the little heat that remains is lost.

A useful shade tree is one that has had ample opportunity to grow through watering and maintenance. A well-pruned tree with lower branches removed but while maintaining a large canopy can be placed close to the sidewalk and provide a greater area of shade and increase the thermal comfort of pedestrians (Helletsgruber *et al* 2020, Pattnaik *et al* 2025). This watering, maintenance, and pruning all come with an economic cost (Hilbert *et al* 2019), therefore there may be fewer shade-providing trees and a resulting greater heat exposure near commuting locations in lower-income neighborhoods.

Understanding the importance of shade can add clarification to other outputs found in figures 7 and 8, especially the divergent effects of buildings on heat exposure in different afternoon bus stop directional aspects. In east-facing bus stops, most direct sunlight occurs at sunrise. This direct solar short-wave radiation can give building materials more time to absorb and store heat energy, which then can re-radiate as sensible heat flux, significantly increasing heat exposure for hours (Liu *et al* 2022). By the afternoon, the stored energy may have re-radiated for hours, therefore increasing the thermal environment even after direct solar exposure ended (Alhazmi *et al* 2022). In contrast, south-facing bus stops showed no significant warming from buildings in the morning because, during summer, less direct solar radiation came from the south in the morning. In the afternoon, buildings provided a cooling effect. This cooling could have occurred due to the shade from buildings reducing the amount of light reaching south-facing locations and lowered the stored energy on the pavement (Zhu *et al* 2023). Together, these findings highlighted the complexities of how urban land cover configurations influenced the human-scale thermal environment differently throughout the day.

It is important to note that while MRT and WBGT identified similar patterns regarding the influence of land cover and bus stop aspect, WBGT responded more weakly to the land-cover drivers of thermal anomaly (figure 8). As WBGT incorporates humidity-dependent physiological constraints, it can be less sensitive to localized radiative modifications from shading or surface temperature. MRT therefore provides a more direct signal of how land-cover configurations alter the radiant environment, whereas WBGT reflects how those conditions translate into bodily heat stress. Using both metrics captures complementary dimensions of commuter heat exposure and has the potential to enhance the ability of health-risk monitoring in vulnerable populations.

Recent studies used machine learning models to examine how land use interacts with the urban microclimate on a human scale (Shandas *et al* 2019, Ibsen *et al* 2024). Because machine learning methods, like random forest, require validation datasets, these studies mainly focused on predicting surface temperatures using SD-LST data or T_{air} from sensor transects. As shown in figure 3 B&E, SD-LST



data did not fully capture how humans experience heat. While T_{air} was a better heat metric for human experience, it only showed minimal differences between sidewalk and shelter exposure for all visits, while MRT had the highest differences of approximately 2.7 °C during morning and afternoons (supplemental figure 1). In our random forest MRT model, high-resolution LST and its variability were the most important factors in both the morning and afternoon (figure 9), reflecting that fine-scale LST patterns, especially those driven by shade variability, are strongly coupled with the radiant environment captured by MRT. However, the source of LST data often lacked the detail needed to describe human thermal exposure accurately. Satellite data, collected perpendicular to the earth's surface, could not capture shade exposure or fine-scale variations like $\text{LST}_{\text{FLIR-SD}}$. For example, at a bus stop, even a small patch of shaded sidewalk can greatly improve comfort (Langenheim *et al* 2020). Tree canopy played a smaller role in predicting MRT compared to LST_{FLIR} . This does not mean tree shade was unimportant. Instead, high-resolution LST equipment more effectively captured shade's position and temperature effects than general tree canopy metrics. A next step could involve studying tree height and canopy configurations at bus stops, such as tree distance from sidewalks, placement around bus stops, or distance from canopy to ground, all of which have shown significant interactions with human thermal comfort (Pattnaik *et al* 2025). Expanding on these details may further highlight important factors of micro-scale LST influences on human-oriented thermal exposure that is missed by SD-LST.

These corrected SD-LST values, combined with land cover data, provided a strong prediction of MRT across the selected sites (figure 10). With this strong model validation and the model no longer requiring high-resolution LST data, we applied the results to locations without Kestrel data. When we modeled MRT at other bus stops within a similar walking distance to the sampled sites, MRT captured more thermal environment variability than using only SD-LST (figure 11). Previously, urban planners using SD-LST to identify bus stops needing heat mitigation would have misidentified locations. For example, in our study, the north-facing bus stop had the highest SD-LST value (41.9 °C), but the west-facing location had the highest MRT value (44.2 °C). Our results also suggested that planners should consider tree planting at east-facing (40.8 °C) or south-facing (40.5 °C) locations first to optimize cooling shade based on bus stop directional aspects.

Next steps and limitations

As noted earlier, the high importance of LST_{FLIR} as a predictor of MRT highlighted the need to capture spatial shade dynamics, such as where shade is cast at what time of day. Improving land cover configuration metrics, such as the positions and clustering of land cover types within the bus stop buffer area, could increase their importance in predicting MRT and WBGT. Furthermore, albedo is known to have a strong influence on MRT (Fang *et al* 2024), and while albedo values can be generally associated with land cover types, future work could benefit from directly collecting albedo values of the surrounding surfaces. These metrics could also better explain when buildings increased or reduced temperatures. If future research lacked access to LST_{FLIR} technology, calculating these configuration metrics could help bridge the gap. Moreover, while MRT appears to be useful for relating heat to shade, in our study the Kestrel sensors used do not have a radiometer, so we were unable to directly tie MRT measurement to

solar light intensity which could help control for meteorological conditions. Also, as we did not measure precise individual-level factors, such as clothing or activity), or assessments of MRT and WBGT are interpretable as a metric of heat exposure, rather than comfort. Future research would be well served by including a radiometer in their sensor deployments. Similarly, with a longer deployment it could be possible to add in more controls for local conditions. While our predictive model is able to control for regional climate, the limited amount of site-specific samples did not allow for comparing different meteorological conditions across all the bus stop data.

We prioritized sampling during hours when commuters were most likely at bus stops, limiting our ability to analyze walking routes to each stop. This introduces two potential limitations. Firstly, we are unable to directly compare the exact recording times of SD-LST (usually occurring at midday) and LST_{FLIR} (recorded a few hours before or after midday). As LST is strongly related to the local land cover and regional weather conditions, the variations we find in LST_{FLIR} across commuting locations are comparable to SD-LST variations at those same locations. However, the magnitude of LST_{FLIR} values compared to SD-LST may be larger or smaller in the afternoon and morning data collections respectively.

As commuting heat exposure includes time spent walking, future studies could benefit from including potential walking routes, or other factors known to influence transit ridership (Chakraborty and Mishra 2013). This limitation also influenced why we only examined income as a measure of inequality. People with different incomes have varying commuting options. On hotter days, individuals with higher incomes might drive to work and pay for parking, or work from home. Whereas individuals with lower incomes might not be afforded those same opportunities due to insufficient vehicle access, working jobs that require them to be physically on-site and/or being more likely to be transit reliant. Expanding future studies to include neighborhood walkability could also make it valuable to consider other demographics, such as race. Numerous examples show how land cover composition varies by race in different neighborhoods. Along these lines, as our study is restricted to specific times of day, we only are able to offer estimations of exposure intensity, and not estimations of exposure duration or frequency. Fully 'human-centric' assessments would require individualized factors to be included (e.g. clothing, physiological activity, and acclimatization) (Nazarian and Lee 2021); which is beyond the scope of a study such as ours that aims to build a more human-oriented heat exposure metric that is generalized across land cover types.

5. Conclusions

In this study, we enhanced urban microclimate research by focusing on the human experience. We achieved this by selecting MRT as the thermal metric, choosing study locations where people are regularly exposed to urban microclimates (commuting locations), and identifying how different populations (based on neighborhood income) faced varying levels of heat exposure risk. Our results show that MRT and WBGT resolved meaningful differences in exposure intensity across bus stops, aspects, and income classes, particularly between sun and shade, even when T_{air} did not differ. A key finding was also that shading amenities interventions (e.g. shelters) produced substantial reductions in MRT, even when air temperature did not differ. This result highlights how radiatively sensitive exposure metrics are useful for planning heat mitigation at commuter locations. We also revealed that bus stop heat exposure depended on total surrounding land cover (which was influenced by socio-economic factors), the bus stop's aspect, and how the configuration of tree canopy and buildings cast shade based on that aspect. Finally, we built a validated predictive model of bus stop MRT. This model showed how urban planners could use our findings to identify locations where heat-mitigating amenities would most effectively reduce commuter heat risk inequality.

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Data availability statement

The data that support the findings of this study is available at the following URL/DOI: <https://doi.org/10.5066/P1FYAHMH>.

Heat Metrics and Model Comparison available at <https://doi.org/10.1088/2752-5309/ae4bfc/data1>.

Conflicts of interest

The authors attest to no conflicts of interest in this publication, and any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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