



METER-SCALE PEDESTRIAN PET AND COOLING-LEVER ATTRIBUTION WITH AN AI SURROGATE: A MICROCLIMATE DIGITAL TWIN FOR A HEAT- RESILIENT BARCELONA SUPERBLOCK

TURNING INCOMING WEATHER INTO PER-STREET HEAT DECISIONS FOR URBAN CLIMATE RESILIENCE

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ABSTRACT

Pedestrian heat stress, expressed as physiologically equivalent temperature (PET), swings across dangerous thresholds within meters as sun, tree shade, and building shadow change, yet weather and satellite data are too coarse to resolve it, and city heat indicators do not map to what a pedestrian feels. For a superblock in Barcelona, we compute meter-scale diurnal pedestrian PET from measurement-driven unsteady CFD (with and without vegetation) and shade-aware radiation post-processing, and validate its air, humidity, and surface-temperature inputs against mobile transects, contact points, and a thermal camera. We decompose street-tree cooling into shade, evapotranspiration, and wind, compare heat measures on one PET metric, and train a machine-learning surrogate that rebuilds the block field in seconds. On a clear July afternoon, after correcting a validated warm-air bias, most of the block reaches strong heat stress; tree cooling is almost entirely shade and concentrates where the canopy shadow falls, while reflective pavement raises pedestrian PET even as it cools the road. The surrogate reproduces the sun/shade field at a thousandth of the cost, a same-day validated microclimate digital twin that maps pedestrian heat at street and hour scale and weighs the city's canopy target, reflective-pavement pilot, and shelter network on one measure.

1. Introduction

Heat waves are the deadliest summer hazard for southern European cities (Royé et al., 2020; Cuervo-Vilches et al., 2023). In Barcelona, on 30 July 2024 the Fabra Observatory reached 40.0 °C, the highest temperature in its record since 1914 (Observatori Fabra, 2024), and during heat waves the risk of death doubles in blocks with little greenery and older housing stock (Xu et al., 2013). What threatens people, though, is the heat load on a body that steps into a sunlit street on a clear afternoon, and that load swings across dangerous thresholds within tens of meters as shade, canyon orientation, and building shadow change.

Barcelona is investing in green corridors, cool shelters, and reflective pavement (Mueller et al., 2020). These initiatives are tracked with aggregate indicators: green space by canopy cover and green area per person; cool shelters by walking time; but no shared indicator shows how shading, irrigation, and reflective pavement affect the pedestrian physiologically equivalent temperature (PET). Each measure impacts PET directly, but because planning units and effects diverge, aggregate indicators cannot determine precisely which street, at what time, and with which measure will hotspots see the greatest temperature reduction for the budget used. A detailed PET map at meter resolution, showing where each measure is effective, is essential.

High-fidelity computational fluid dynamics (CFD) can achieve this resolution, but with current computing resources, a single simulation can take tens of hours, making it impractical to compare numerous planning options. This study addresses that challenge by developing a high-resolution PET model validated with field data, then using it to train a rapid AI surrogate. This AI model reconstructs the detailed PET field from coarse inputs in seconds, serving as a proof of concept. The surrogate then rebuilds the block's pedestrian PET in seconds for any hour, work that takes the CFD hours.

1.1. Southern European heat and the unit that measures it

The health effects of heat waves are well understood. Studies across Spain's major cities indicate that natural deaths and emergency transports increase significantly during heat-wave days. In coastal cities, this impact is linked to the minimum temperature ($T_{\min}$). Within a single city, the effect also varies greatly by factors such as socioeconomic status, building age, and greenery, as noted by Royé et al. (2020), Cuervo-Vilches et al. (2023), and Xu et al. (2013). This block-level variability highlights the importance of treating heat risk as a distribution rather than a single city-wide average.

Urban drivers are also quantified. The urban heat island (UHI) intensity of metropolitan Barcelona averages about 2 °C annually and peaks at night (Martin-Vide & Moreno-Garcia, 2020). Heat-wave UHI drivers in European cities (city size, climate zone, green fraction) have been cataloged (Ward et al., 2016). For metropolitan Barcelona, satellite data show a relationship between nighttime surface temperature and greenery (Arellano & Roca, 2022). An analysis of 85 European cities estimates the economic loss from UHI-attributable excess mortality (monetized using the value of a statistical life) at €192-314 per resident per year (Huang et al., 2023). Reviews of urban overheating (Santamouris, 2020; Heaviside et al., 2017) support the benefits of mitigation. Heat risk is hidden within the city average and appears as a within-block distribution, strongly governed by greenery and solar radiation.

A pedestrian's heat load depends on more than air or surface temperature. It is influenced by air temperature, relative humidity (RH), wind speed, and the mean radiant temperature (MRT), which combines solar and longwave radiation from surrounding surfaces. On clear days, MRT is the most significant factor. The PET simplifies this complex combination into a single temperature value using a human energy-balance model (Höppe, 1999; Matzarakis et al., 1999). Building on the Munich Energy-balance Model for Individuals, PET is the air temperature of a standard reference environment (still air, no added radiation, moderate humidity) at which a person's core temperature, skin temperature, and sweat rate match those in the setting being assessed. Therefore, its units are °C, and planners and residents can intuitively understand it. A

comprehensive review of outdoor heat perception indicates that of 165 indices, four are commonly used: PET, UTCI, PMV, and SET*, with PET representing them (Potchter et al., 2018; Staiger et al., 2019). We choose PET and, to avoid overconfidence in point estimates, report it according to Matzarakis's heat-stress categories: 29–35 °C (moderate), 35–41 °C (strong), and above 41 °C (extreme). Using these categories aligns well with our methodology, which derives MRT from a radiation model, and accounts for the variation in comfort ranges across climate zones (Krüger et al., 2017; Chen & Matzarakis, 2017).

1.2. Four gaps to close: resolution, pathway, policy, speed

Connecting heat-risk distribution to measure selection requires addressing four gaps simultaneously.

First, consider resolution. Weather data usually cover entire neighborhoods or cities, while satellite land surface temperature (LST) provides detailed information at 30–100 m resolution. Neither method captures the few-meter PET variation a pedestrian experiences. LST shows surface temperature, not the MRT or PET a pedestrian perceives. In real-world scenarios, PET can vary by meters within the same intersection, influenced by factors such as sun, street-tree shade, canyon orientation (east–west vs. north–south), and building shadows. Urban microclimate CFD can achieve this resolution (Toparlar et al., 2017), but many studies stop at pedestrian wind speeds, use steady-state Reynolds-Averaged Navier-Stokes (RANS) equations that don't capture the full diurnal cycle, or treat radiation and MRT separately, which prevents accurate PET assessment. Fully unsteady CFD simulations over a full day, validated against measurements, are rare. Notable examples include Antoniou et al., 2019, and Chen et al., 2025.

Second, the cooling pathway. The lowering of PET due to greening has been repeatedly demonstrated using ENVI-met (Bruse & Fleer, 1998) and CFD (Teshnehdel et al., 2020; Detommaso et al., 2021; Sabrin et al., 2021; Jia & Wang, 2021). Street-tree cooling involves three physically distinct pathways: (i) canopy shading that reduces solar radiation and MRT, (ii) latent heat from evapotranspiration (ET) that decreases air temperature, and (iii) lower wind speeds caused by canopy drag, affecting convection and ventilation. Identifying which pathway dominates depends on the optimal layout, species selection, and irrigation strategy (species dependence, e.g., Vatani et al., 2024). Most literature reports the combined net effect on air or surface temperature, but studies distinguishing these pathways within PET units are rare. Radiation-resolving models indicate that tree benefits mainly stem from MRT reduction with minimal impact on air temperature (Lachapelle et al., 2023). Different contributions of trees and water bodies have been documented (Yang et al., 2025), yet few studies link pathway decomposition to policy measures. Evaluations comparing measures like street trees, shade structures, and reflective pavement on a single pedestrian PET metric are scarce, and reflective pavement, while lowering road-surface temperature, can reflect shortwave radiation back to pedestrians and increase heat load (Erell et al., 2014; Schneider et al., 2023; Mohammad et al., 2021).

Third, the policy connection. Urban heat mitigation efforts are often discussed using area-based targets such as green space per person, canopy cover percentage, and deaths prevented. These indicators rely on broader area metrics that differ in granularity and units from the PET a person experiences on the street. For example, Barcelona's cool-shelter network ensures that 98% of residents are within a 10-minute walk to a shelter (Pede, 2024). However, the specific heat exposure experienced on the walk to a shelter along individual routes is not mapped. What remains unaddressed is how to link these area-wide targets to specific street segments at particular times, using appropriate measures to reduce PET hotspots.

Fourth, speed. High-fidelity CFD with radiation post-processing takes tens of hours for a full-day case, making it unsuitable for comparing multiple design options (species, layout, pavement). Machine-learning surrogates reportedly accelerate CFD by hundreds to thousands of times (Caron et al., 2025; Mao et al., 2025; Zhao et al., 2024). Advances such as meso-to-micro downscaling (Javanroodi et al., 2022) and city-wide 1 m UTCI generation (Briegel et al., 2025) have emerged. However, most approaches either (a) learn wind and air temperature from

idealized arrays, (b) use ENVI-met as training data, or (c) do not produce outputs that include a comfort index. Finding a surrogate trained on Fluent-RANS data (covering radiation and leaf area density (LAD) sources), targeting PET in a real block and validated against measurements, remains difficult. Machine learning studies on PET prediction (Jung et al., 2026; Mohite & Surawar, 2024; Alinasab et al., 2025) also rely on ENVI-met or local regression rather than high-fidelity CFD.

Picking the right measure for one street at one hour means comparing pedestrian-comfort measures at that resolution, quickly, and against field data. No current method does all four, so we build one.

1.3 Objectives and contribution

This study asks how a block's trees, paving, and built form turn the day's weather into the heat a pedestrian feels, and which measures cut that heat, where and when. It also asks whether the field can be rebuilt fast enough to be used.

We compute meter-scale pedestrian PET across a full day for a real Barcelona superblock. An unsteady CFD solves the wind, air temperature, humidity, and tree evapotranspiration. A geometric shade model adds the canopy's blocking of direct sun, which the CFD omits and which sets comfort on a clear day. We check the results the same day against three instruments: air temperature and humidity from mobile transects, wall-surface temperature from a contact sensor, and ground-surface temperature from a thermal camera. In this field, we split tree cooling into shade, evapotranspiration, and wind, and we place trees, reflective pavement, and shelter access on one pedestrian measure. A surrogate rebuilds the field in seconds, so planners can screen the canopy plan, the reflective-pavement pilot, and the shelter network at the scale of a street and an hour. We report PET by heat-stress class and by its difference between cases, not as a single number.

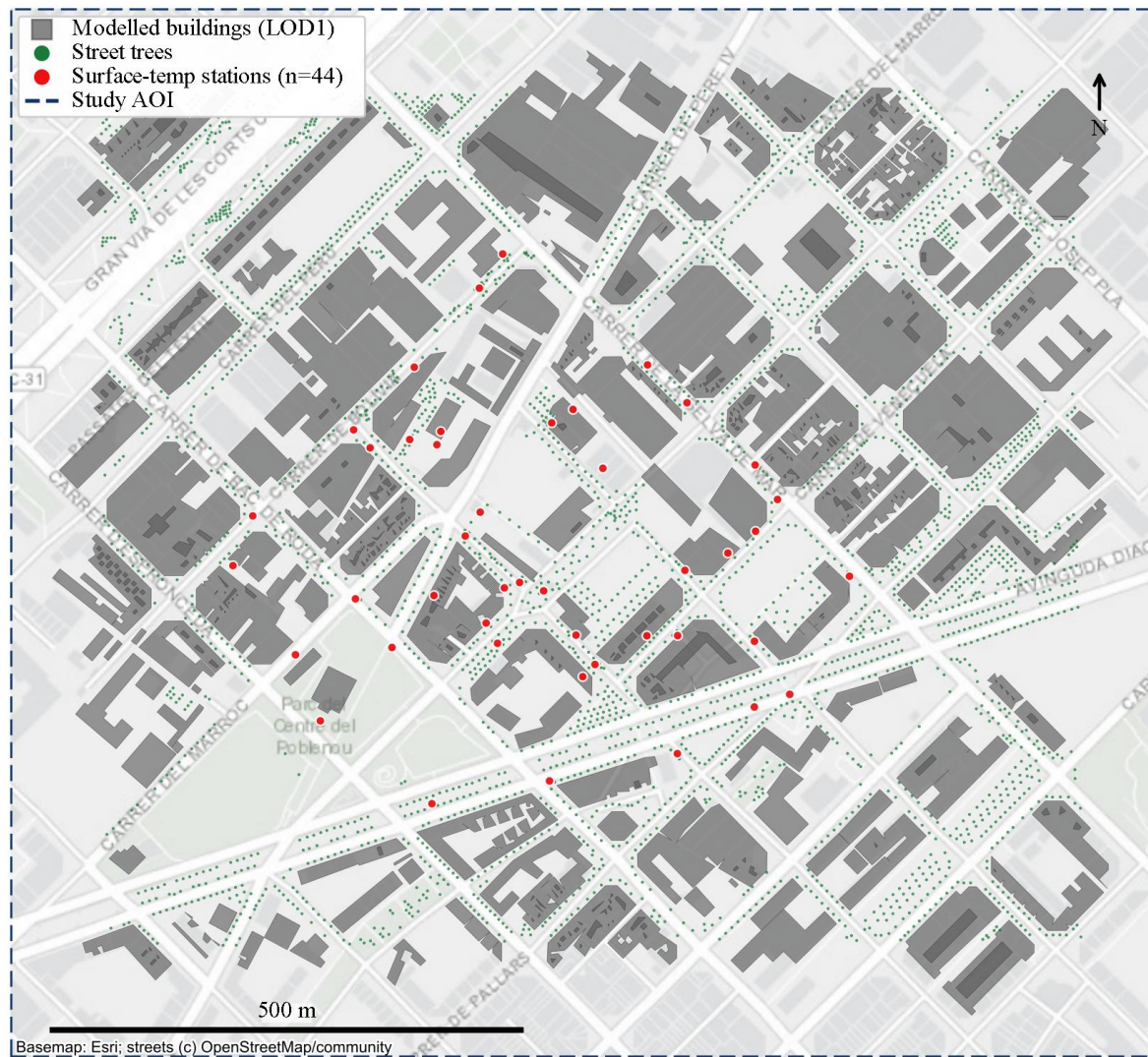
2. Study area and data

2.1 Study area

Poblenou is a redevelopment zone in Barcelona's Sant Martí district, featuring a dense urban grid based on the 19th-century Cerdà plan, with 113×113 m blocks and chamfered corners (Fig. 1). The specific block studied is the Ca l'Alíer superblock, which the city has designated a 'Barcelona Sandbox'. Part of the 22@ initiative, it aims to convert former industrial areas into a hub for knowledge industries, combining historic and modern structures, including high-rise buildings. Its Mediterranean climate (Köppen Csa) entails hot summers with strong sunlight, light winds, and daytime sea breezes. Although proximity to the Mediterranean results in somewhat cooler temperatures during heat waves compared to inland regions, extensive hard paving and limited street-tree coverage amplify solar exposure and the urban heat island effect at pedestrian level.

Three main reasons determine the choice of this district. First, Poblenou was the site of the first superblock (superilla) introduced in 2016 (Mueller et al., 2020), acting as a pilot for greening strategies. A Barcelona superblock groups about nine Cerdà blocks (5,000–15,000 residents), dimensioned so that most of the services its residents use are provided within it. Second, the city's vulnerability map shows limited access to public green spaces, indicating a clear need for intervention. Third, an independent field campaign described below gathered pedestrian-level data to support CFD validation. The study focuses on a detailed analysis of a single block and does not aim to extend the results to the entire city.

Figure 1. Study block, the Ca l’Alier superblock, Poblenou (Sant Martí, Barcelona): 22@ redevelopment on the Cerda grid, area of interest and building massing.



Source: this study, GIS.

2.2 Geometry

Buildings are modeled at LOD1, displaying footprints and height prisms. To maintain visual continuity and shadows of high-rises, each tall building is kept at its accurate height individually, while low-rise buildings within the same block are combined into a single mass, creating a tower-preserving reconstruction. This preserves the main shapes influencing canyon shadows and flow, while reducing the total number of cells. Building footprints are sourced from city data, with heights calculated from both that data and LiDAR. Tree canopy detection involves processing classified LiDAR data (AMB, 2022) with PDAL to isolate tree points, because a digital surface model (DSM) can misrepresent trees as buildings. This results in canopy footprints and tree heights. The area of interest (AOI) surrounds the target blocks and defines the computational domain, including inflow, outflow, and top-clearance boundaries. Ground within and outside the AOI is separated, and these zones, along with buildings, inflow, and top, are used for boundary conditions and sampling during post-processing.

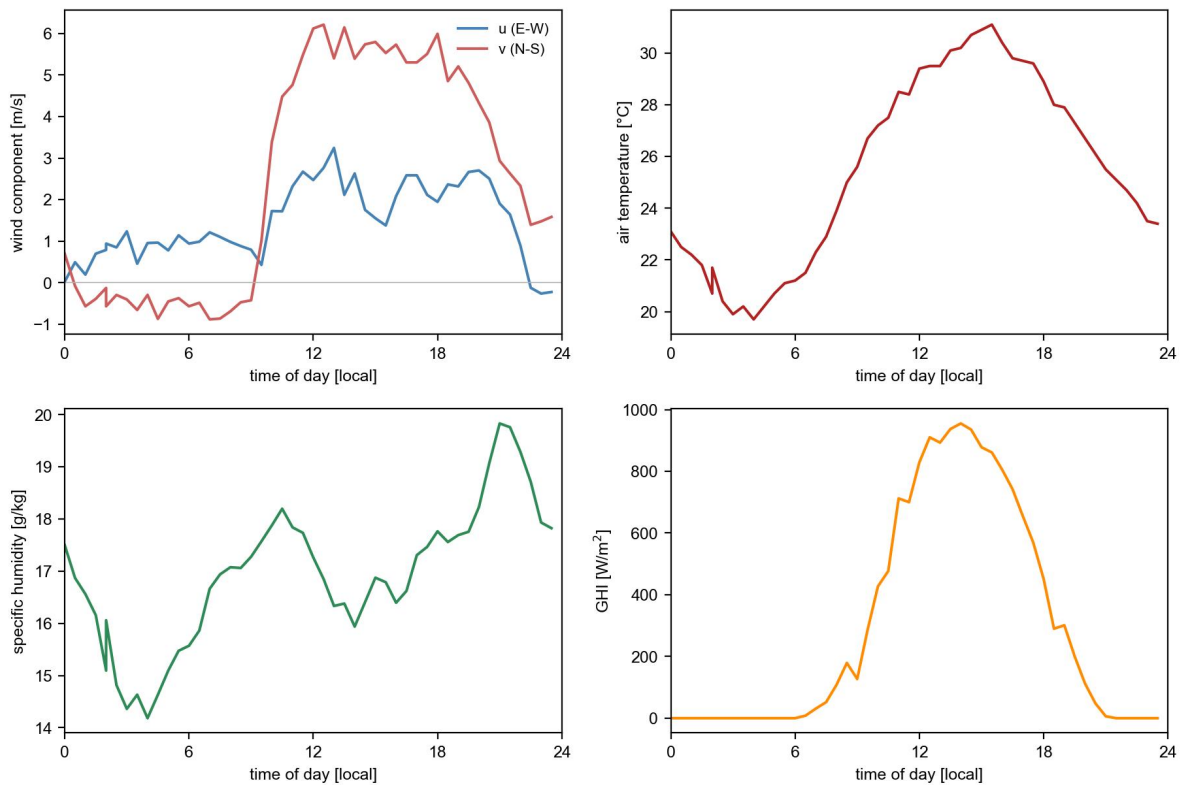
2.3 Weather forcing

The inflow boundary uses time-series profiles derived from Meteocat measurements at El Prat / the city XEMA reference station (Fig. 2), including the two horizontal wind components (u , v), air

temperature, specific humidity (water-vapor mass fraction), global horizontal irradiance (GHI), and sky temperature. For each time point, these are given as vertical profiles of the atmospheric boundary layer (ABL). Wind speed is extrapolated with height using a power law (exponent $\alpha=0.28$) from a reference height of 10 m and a reference speed of 3.91 m/s, and turbulence quantities (k and ϵ) follow equilibrium ABL relations. The diurnal sea breeze cycle (which intensifies from seaward in the afternoon) and daily variations in air temperature, humidity, and GHI provide six time-dependent boundary-condition profiles. The series is recorded at 30-minute intervals and interpolated for the CFD at each 300-second time step.

The reference day is the field campaign day (2026-07-30), characterized by clear skies and intense solar radiation. The inflow profile is derived from that day's weather measurements, ensuring the model and validation observations correspond to the same date. A clear day is selected because solar shading and MRT become the dominant factors, allowing the different measures, greening, shading, and pavement, to be most distinctly separated. Reproducing overcast conditions, multi-day patterns, or heatwave events is beyond the scope of this study.

Figure 2. Diurnal inflow forcing on the reference day (2026-07-30): horizontal wind components, air temperature, specific humidity, and global horizontal irradiance; local time.

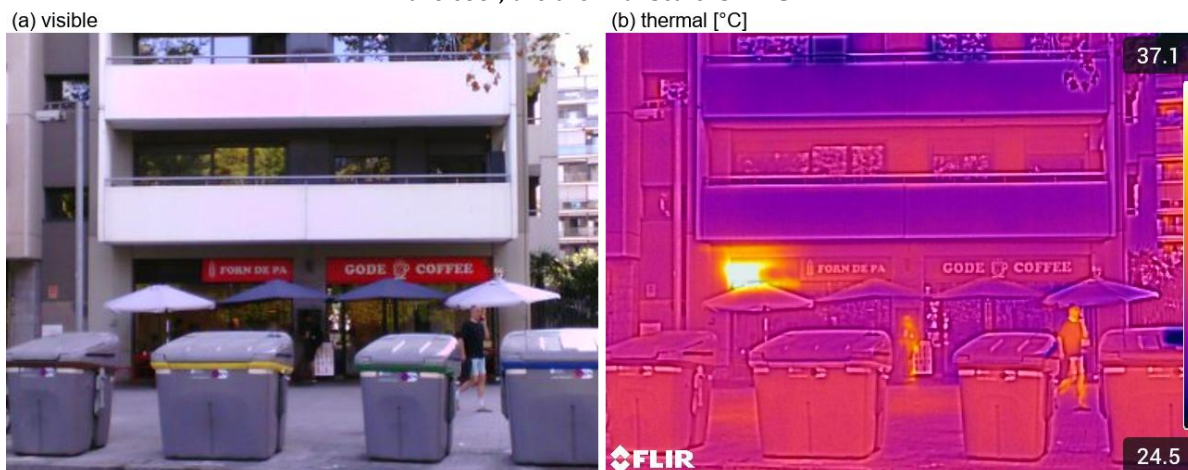


Source: Meteocat.

2.4 Field campaign

Field observations on July 29-30, 2026, gathered three data streams. During mobile transects, handheld sensors (Brochhagen & Arefi, 2026) recorded continuous air temperature, relative humidity, and pressure along the walking route, yielding about 1,100 points during the day and 700 at night across four calibration walks, all GPS-tagged. Contact measurements repeatedly assessed surface temperature at 44 GPS-tagged points, totaling around 11,000 samples. A FLIR E8 Pro thermal camera added radiometric surface-temperature images of walls and ground (Fig. 3), cross-checked against the contact sensor (MBE about 0). Times are synchronized with the CFD in UTC, and GPS coordinates are transformed into the CFD frame. Air temperature and relative humidity directly validate PET inputs, while surface temperature validates radiation and ground balance.

Figure 3. Field-campaign example on the reference day: (a) visible photograph and (b) FLIR thermal image of the same Poblenou street. Sunlit ground and containers are warm while shaded areas and canopy are cool; the thermal scale is in °C.



Source: this study.

3. Methods

3.1 Unsteady CFD setup

In Ansys Fluent 2025R2, using 3D double precision, the unsteady RANS equations are closed with the realizable $k-\varepsilon$ turbulence model and standard wall functions, where mean y^* is approximately 90–120 near pedestrian level within the log-law region. In addition to conserving mass, momentum, and energy, we solve a two-species transport equation for air and water vapor. Buoyancy effects are approximated using the Boussinesq approximation (reference density 1.225 kg/m^3 , temperature 288.16 K), with gravity acting downward (gravity $g = -9.81$ in the z direction). Since urban RANS accuracy depends on the turbulence model and ground roughness (Ricci et al., 2020), we use the realizable $k-\varepsilon$ model with wall functions, second-order upwind advection, and SIMPLE pressure-velocity coupling. The model domain, blockage ratio, upstream/downstream lengths, lateral/top clearances, and boundary conditions follow urban wind-engineering best practices (Franke et al., 2007; Tominaga et al., 2008), a rectangular domain with a 2.8% blockage ratio, at least 5H upstream and 15H downstream clearance, and at least 5H lateral and top clearance ($H \approx 117 \text{ m}$, the tallest building), and are aligned with a validated pedestrian-wind record (Blocken et al., 2009). Boundary conditions include the inflow velocity profile; outflow pressure and sky temperature; top-boundary symmetry and sky; and ground and building surfaces modeled as energy-balance walls with material-specific heat capacities and thermal conductivities. Surfaces take a solar absorptivity of 0.7 for the ground and 0.6 for walls (albedo 0.30 and 0.40), with multilayer shell conduction to a fixed deep-soil and indoor backing temperature. To avoid decay of the inflow profile downstream using standard wall functions with an equilibrium ABL, we verified horizontal homogeneity of the vertical profile in an empty domain (maintaining u , k , ε between inflow and the upstream AOI). We set the roughness length and wall-function parameters according to the Richards-Hoxey/Blocken consistency condition (Blocken et al., 2009).

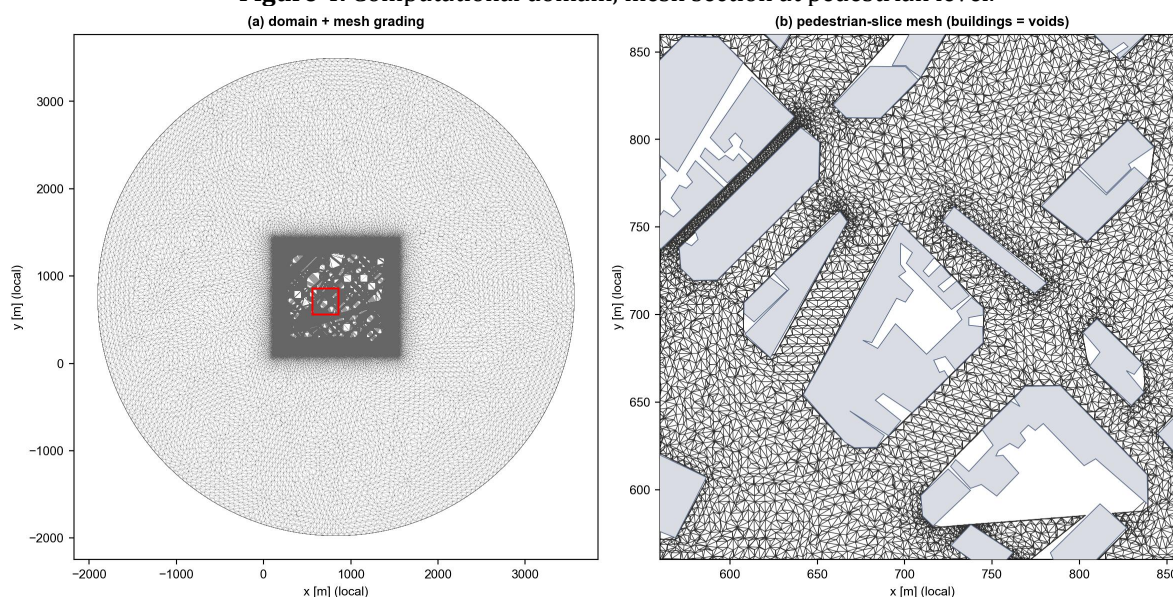
We used dual-time-stepping with a physical time step of $dt = 300 \text{ s}$ and 40 inner iterations per outer step, covering a full 24-hour period. After testing inner-iteration counts of 20, 40, 60, and 100, 40 was chosen once continuity and energy residuals stabilized sufficiently at each outer step, balancing accuracy and computational efficiency. Since the canopy source terms are stiff, k and ε are excluded from the convergence check, which focuses on continuity and energy. A staged startup sets up a stable radiation and temperature field before the diurnal cycle: (1) initialize at a high-sun time (flow-time $50340 \text{ s} \approx 14:00$) to develop a non-degenerate radiation and temperature field, (2) reset the clock to 0:00, (3) with canopy sources off and radiation updated every 10 iterations, increase the time step in stages 0.5, 1, 5, 30, and 60 s to allow

transient adjustment, and (4) restore second-order accuracy, turn on canopy sources, and run the 24-hour cycle at $dt=300$ s. The 14:00 time is for building the initial conditions based on the solar position, not the start time; the simulation covers hours 0–24. Table 1 summarizes the main numerical and boundary settings for reproducibility.

3.2 Mesh and domain

The domain is discretized at two different resolutions, approximately 2.1 million and 9.4 million cells (refinement ratio ~ 1.6), for the grid-convergence analysis. The production runs use the coarser level (around 2.1 million cells), featuring a tower-preserving unstructured mesh graded toward the pedestrian level (see Fig. 4, Table 1).

Figure 4. Computational domain, mesh section at pedestrian level.



Source: this study.

3.3 Radiation and sun

Radiation is addressed using the DO method in a gray (wavelength-unresolved) format, with the solar load calculated via a Fair-Weather solar model. The solar position is determined for each time step using a latitude of 41.40°N , a longitude of 2.19°E , and a reference day that cycles with flow time. Solar radiation, both direct and diffuse, enters through a semi-transparent top boundary and is absorbed by buildings, the ground, and (in case of vegetation) canopy cells, heating these surfaces. The longwave emission from these heated surfaces is redistributed within the DO field and returns to the air temperature field through the wall energy balance. To reduce computational demands, radiation is updated every 10 iterations (see Table 1).

We choose DO because it handles multiple reflections in complex geometries and a semi-transparent sky stably, and because surface temperature and MRT accuracy are sensitive to model choice (DO/S2S/P-1) (Chen et al., 2025). Longwave sky radiation is handled by the gray DO default. The with-vegetation and no-vegetation cases use identical radiation settings, so their difference is attributable solely to vegetation sources.

Gray DO accounts for building shadow, ground and wall-surface temperature, and environmental longwave radiation, but it does not consider canopy shading of direct solar radiation (tree shade), the term that governs clear-day comfort. We add this tree shade afterward using a geometric shade model outside the CFD. The MRT and PET formulations are based on the human radiation-balance model family (Fröhlich & Matzarakis, 2020).

3.4 Vegetation (LAD volume sources)

The vegetated run models the canopy as a porous medium by adding leaf-area-density (LAD) volume sources to the governing equations: a leaf-drag momentum sink, Sanz-family turbulence production and dissipation, a transpiration water-vapor source, and a latent-heat sink ($C_d=0.2$, $\beta_p=1.0$, $\beta_d=5.1$, $C_{\epsilon 4}=C_{\epsilon 5}=0.9$), with a spatial LAD from classified-LiDAR canopy footprints and i-Tree leaf data injected per cell through a user-defined function; transpiration is prescribed as a steady species-specific rate under adequate irrigation. The unvegetated baseline disables all these sources, so differencing the two runs isolates the evapotranspiration and canopy-drag pathways, while canopy shade is added geometrically in post-processing.

3.5 Shade-aware PET (post-processing)

The CFD does not include canopy radiative shading (tree shade). Because clear-day PET is governed by MRT, and MRT by the shading of direct solar radiation, tree shade is injected in post-processing by a geometric shade model (SOLWEIG/RayMan family; Lindberg et al., 2008; Matzarakis et al., 2009). The procedure is summarized in Fig. 5 and detailed below.

1. Direct/diffuse split: the boundary GHI is split into direct horizontal and diffuse components with the Erbs correlation (Erbs et al., 1982). The solar position is computed on the same calendar and UTC as the CFD.
2. Occlusion test (beam-reach factor): from each pedestrian point ($z=1.1$ m), a ray is cast toward the sun, and intersection with the LOD1 buildings and the canopy footprints (with heights) determines sun or shade, giving a direct-reach factor *beam_factor* $\in [0,1]$. The canopy is approximated as opaque (foliage transmittance can later be extended to an LAD-dependent transmittance).
3. Sky view factor (SVF): at each point, hemispheric rays are sampled to obtain the fraction of sky not blocked by buildings and canopy; SVF (total SVF and the canopy contribution *svf_can*) is used as the visible-sky factor for diffuse and longwave radiation.
4. MRT composition: direct radiation on the body is projected onto a spherical body with a projected-area factor f_p (dependent on solar elevation and azimuth) and superimposed with diffuse, ground-reflected, and longwave (environmental surfaces and sky) radiation to obtain the mean radiant temperature (MRT). To avoid double-counting longwave radiation, environmental surface temperatures use CFD ground and wall temperatures, and air and sky longwave use CFD air and sky temperatures as a first approximation.
5. PET calculation: with MRT and the CFD air temperature, specific humidity, and wind speed as inputs, PET is obtained from the Höppe/Matzarakis human energy balance (standard person, metabolic rate *met* 1.38, clothing *clo* 0.9) (Höppe, 1999).

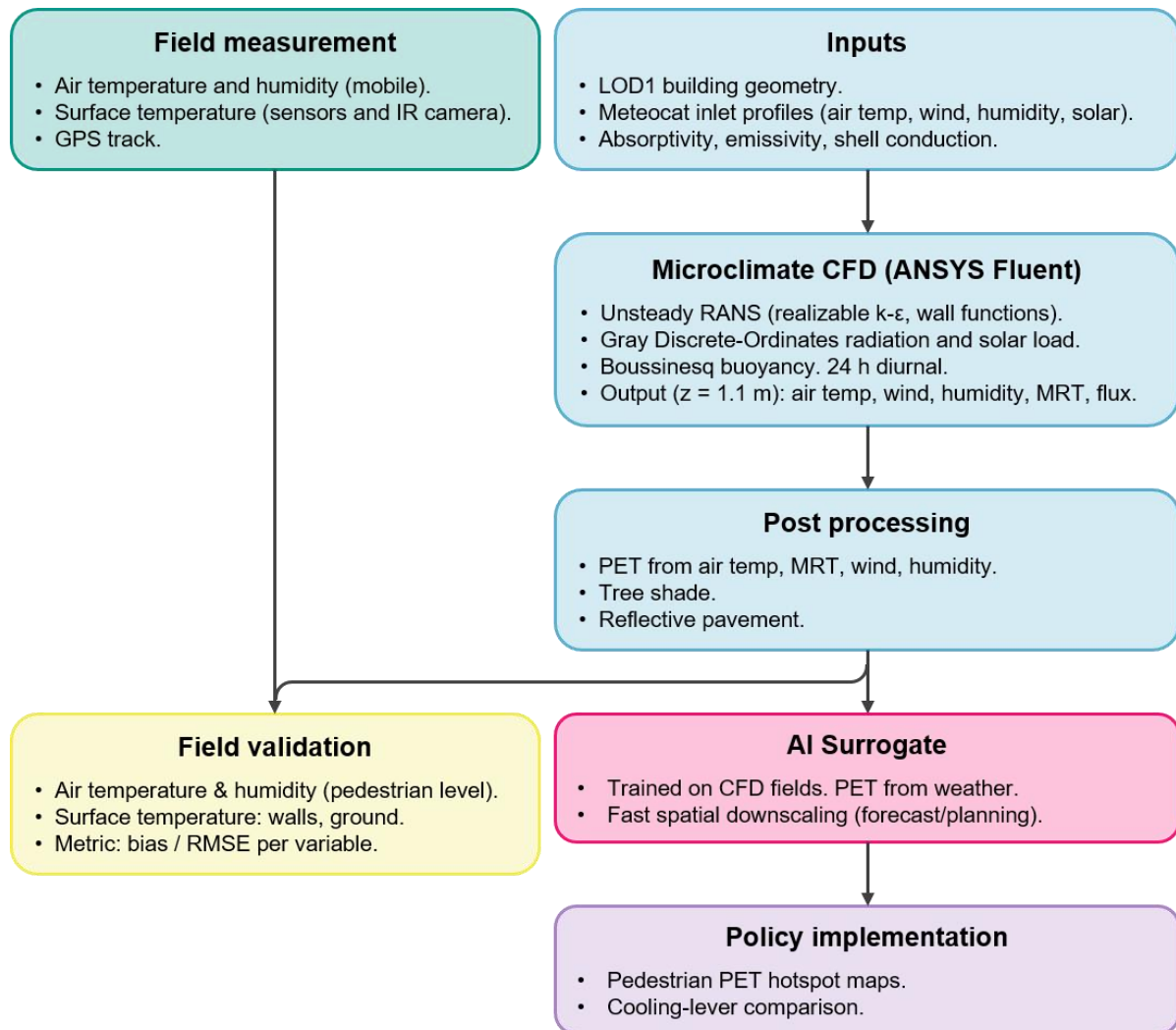
This split design (the CFD for wind, air temperature, humidity, and ET; the radiation model for shade, SVF, and MRT) sits in the Eddy3D / RayMan+SkyHelios lineage (Fröhlich & Matzarakis, 2020), and its point is that a geometric model supplements only the one radiative-shading pathway the Fluent canopy cells cannot carry.

3.6 Cooling-pathway decomposition and policy levers

Clear-day pedestrian comfort depends on MRT, which is influenced by direct-sun shading. The study breaks down the effect of street trees into different pathways and compares them using a single PET metric across various pedestrian-scale interventions. These scenarios include a baseline without vegetation or interventions; trees providing shade, evapotranspiration, and wind; a shade-only scenario; a combined ET+wind scenario; and a cool-pave option with increased ground albedo from 0.30 to 0.55. Shade serves as a stand-in for the MRT impact of overhead canopies, though actual structures differ in sky view and longwave re-emission and require separate modeling. Cool-pave effects are evaluated independently by adjusting reflected shortwave calculations; because the radiant longwave term uses the CFD air temperature rather than the pavement surface temperature, this captures the added reflected shortwave but omits the offsetting longwave cooling from the cooler pavement, so the estimate is an upper bound on

the pedestrian warming. Reflective pavements can increase PET by returning shortwave radiation to pedestrians, even as they cool the pavement surface. We validated the assumption of additivity among pathways, with the combined pathways closely matching the total tree effect within measurement noise on this clear day. For the shelter analysis, we take Barcelona's climate-shelter (refugis climàtics) locations from Open Data BCN, keep those within the block and a 400 m walkable buffer, and map each pedestrian node's distance to the nearest shelter on the afternoon-peak PET field (Fig. 12).

Figure 5. Method flow.



Source: this study.

3.7 AI surrogate

Running CFD plus shade post-processing can take tens of hours for a full-day case and isn't efficient for comparing many options. Instead, we use high-resolution PET field data (pedestrian-level, $z=1.1$ m, at 30-minute intervals) to train a lightweight gradient-boosted-tree surrogate. This model quickly reconstructs the same block's areal PET from coarse inputs. The input features include physically meaningful quantities such as cyclic time encodings (*hour_sin*, *hour_cos*), solar azimuth and elevation (*az_sin*, *az_cos*, *elev*), boundary weather data (*amb-Ta*, *amb-h2o*, *amb-wind*, *GHI*, *DNI*, *DHI*), local geometry metrics (sky view factor *svf_total*, canopy contribution *svf_can*, distances to the nearest building and canopy, and canopy flags), ground albedo, and the beam-reach factor from geometric occlusion. Additionally, because radiation and

shading dominate per prior research (Cui et al., 2025; Alinasab et al., 2025), we include effective radiative flux as explicit features: direct radiation (*beam_DNI*), diffuse radiation (*diff_recv*), and a longwave proxy (*lw_deficit*). The model primarily relies on a gradient-boosted tree, combined with a linear, physics-based component that accounts for forcing dependence within the training range, following Caron et al. (2025). This linear base aids interpolation but may not extrapolate well to unseen extremes.

This proof of concept focuses on spatiotemporal interpolation within the same block and day, without claiming the ability to extrapolate to unseen block geometries, different weather conditions, or alternative designs, which remain future work. The evaluation aligns with the use case: during operation, weather variables such as air temperature, wind speed, and solar radiation are provided as known inputs, making the task one of spatial downscaling at a specific time or interpolation. The operational metrics include (i) a spatial block holdout, which divides the AOI into quadrants; this is a true spatial test that does not rely on x and y coordinates as features, and (ii) a random holdout, considered the main test; alongside this, (iii) a time holdout excludes peak hours to assess performance under unseen forcing conditions. Because a naive split that randomly removes nearby points can overestimate R^2 due to spatial autocorrelation, we emphasize spatial block testing. We assess prediction validity using Shapley additive explanations (SHAP) and permutation importance, which show that the most influential features are *beam_DNI*, *build_dist*, and *SVF*-type, aligning with the physics in which radiation and shading influence PET. However, because *beam_factor* and *SVF* are also used in the post-processing that creates the training PET, high accuracy partly reflects underlying analytical relationships. To evaluate the true learning contribution, we also present results with only coarse inputs, excluding occlusion features.

Microclimate ML surrogates are reported at hundreds-to-thousands-fold speedup and $R^2 \approx 0.9$ (Zhao et al., 2024; Javanroodi et al., 2022; Briegel et al., 2025; Ignatius et al., 2024), and for PET there are high-accuracy tree models trained on ENVI-met (Jung et al., 2026; Mohite & Surawar, 2024; Alinasab et al., 2025). This study is significant because the training data are Fluent-RANS (DO radiation plus LAD) plus shade post-processing, targeting a PET field cross-checked against measured air temperature, RH, and surface temperature in a real block. The generalization limit (weak extrapolation to unseen morphology) is known and stated (Wang et al., 2025; Caron et al., 2025).

Table 1. Numerical, boundary, and material settings

Category	Item	Setting
Solver	Code/precision	Ansys Fluent 2025R2, 3D double precision, unsteady RANS
Turbulence	Model/wall	Realizable k - ϵ , standard wall functions (pedestrian-level $y^* \approx 90$ –120)
Mesh	Type/cell count	coarse_wf, about 2.10×10^6 cells
Buoyancy	Approximation/reference	Boussinesq; $\rho_0 = 1.225 \text{ kg/m}^3$, $T_0 = 288.16 \text{ K}$, $p_0 = 101325 \text{ Pa}$, $g = -9.81 \text{ m/s}^2$
Composition	Species	Two-species transport of air + water vapor (H_2O)
Air properties	c_p / k	1006.43 J/kg·K, 0.0242 W/m·K
Radiation	Model	Discrete Ordinates (gray), radiation update once per 10 iterations
Sun	Method/position	Fair-Weather solar load; latitude 41.40°N, longitude 2.19°E, July 30, 2026, cycling with flow-time
Time integration	dt / iterations	dt=300 s, dual-time 12 outer/hour $\times$ 40 inner, 24 h
Discretization	Advection/coupling	Momentum second-order upwind (after ramp), k - ϵ first-order, SIMPLE family
URF/limits	Relaxation/cap	During the diurnal cycle $k=\epsilon=0.5$, turb-visc 0.5; turbulent-viscosity ratio cap 1×10^5

Category	Item	Setting
Convergence	Residuals	Continuity 1×10^{-3} , velocity 1×10^{-4} , energy 1×10^{-6} ($k \cdot \varepsilon$ excluded from the check)
Boundary	Inflow	Velocity profile (power law $\alpha=0.28$, $U_{\text{ref}}=3.91$ m/s at $z_{\text{ref}}=10$ m), air temperature, H ₂ O mass fraction, GHI/sun, sky temperature
Boundary	Ground and buildings/ outflow and top	Energy-balance walls with shell conduction (multilayer, material-specific c_p , k , deep/indoor backing temperature) / pressure outflow, symmetry top (sky longwave by gray DO default)
Vegetation	LAD source constants	$C_d=0.2$, $\beta_p=1.0$, $\beta_d=5.1$, $C_{\varepsilon 4}=C_{\varepsilon 5}=0.9$ (UDF injection); transpiration prescribed
Computing resources	Nodes/memory	1 node, 8 cores, 150 GB, output at 30-minute steps

Source: This study.

4. Validation

4.1 Mesh independence

A grid check comparing coarse and fine resolutions at midday shows that discretization impacts the results. The average pedestrian PET for the AOI differs by 8.3% between the two mesh types (coarse ≈ 2.1 M cells at 45.6°C, fine ≈ 9.4 M cells at 42.1°C during peak conditions), indicating a conservative convergence index of about 14%, based on a second-order assumption and a safety factor of 3 (Roache, 1994). This suggests the true PET value has uncertainty of a few kelvin, in addition to the canyon-air bias. The heat-stress indicator is less affected by grid size: the area with PET $\geq 35^\circ\text{C}$ shifts by only 0.3 percentage points between meshes, and the finer split between strong and extreme stress levels varies more but is not based on absolute counts. Since the main conclusions depend on the boundary between strong and extreme stress and on PET differences evaluated on a single mesh, where common discretization errors cancel out, the coarse mesh is sufficient for ranking and signing the policy levers, with the understanding that absolute PET values should be interpreted with this caveat. Because each lever is a difference taken on one mesh, discretization error is common-mode and cancels in dPET; the strong-or-extreme area shifts by only 0.3 percentage points between grids, so the sign and ranking of the levers are grid-independent even when the absolute PET is not. The two-grid Richardson estimate therefore bounds the absolute PET uncertainty rather than removing it, consistent with reporting by heat-stress class and by dPET.

4.2 Multi-variable validation against measurements

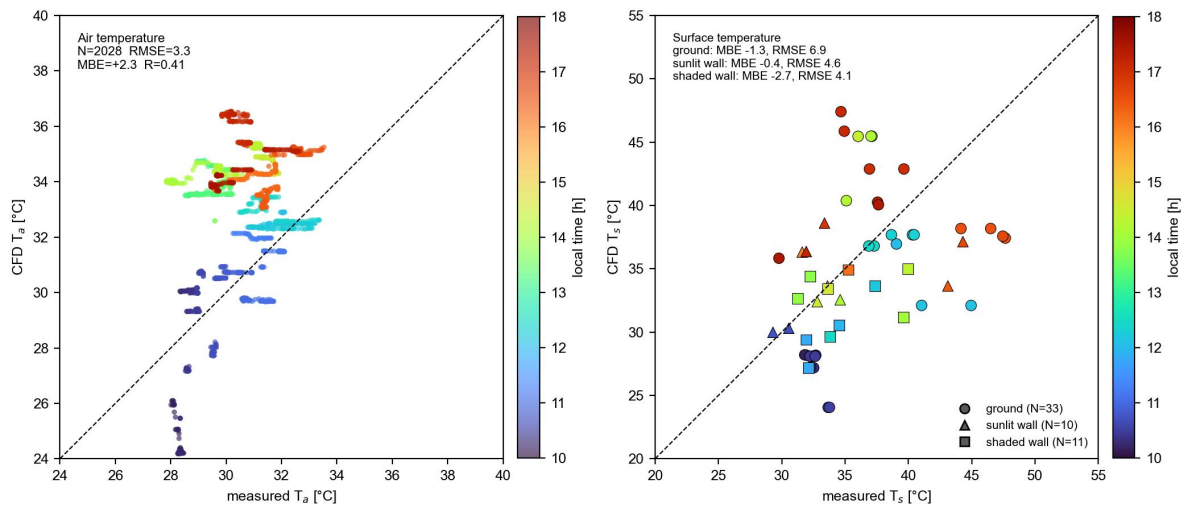
Of PET's four inputs, air temperature and relative humidity were measured along the mobile transects, with wall-surface temperature from a contact sensor and ground-surface temperature from a FLIR thermal camera cross-checked against the contact sensor (MBE about 0). The CFD model was validated against these measurements (Fig. 6), showing good agreement: sunlit facades differ by -0.4°C (RMSE 4.6, $N=10$), shaded facades are about -2.7°C cooler (RMSE 4.1, $N=11$), and ground points (thermal camera) differ by -1.3°C (RMSE 6.9, $N=33$). This suggests CFD reliably models hot sunlit facades and tends to slightly underestimate shaded and ground temperatures. Relative humidity, which correlates with air temperature, closely matches the transects (modeled mean 54% RH, MBE -0.6 percentage points) and is not separately shown. The main residual discrepancy concerns street air: CFD predicts it to be $+2.3^\circ\text{C}$ warmer during the day (RMSE 3.25, R^2 0.41), increasing to about $+3.5^\circ\text{C}$ at midday and decreasing to around -2°C near dawn. The CFD thus overstates the diurnal range, warm by day and cool by dawn. One mechanism explains both signs: weak canyon ventilation holds heat near the ground under strong daytime radiation and holds the radiatively cooled air through the night, and the model carries no anthropogenic heat to buffer the pre-dawn minimum. Since the inflow profile already

accounts for sea-breeze cooled air (noon 30.2 °C, matching street measurements), the temperature excess develops inside the canyon. Weak canyon ventilation causes hot ground to influence near-surface air. Since $\partial\text{PET}/\partial T_a$ is approximately 1.2, this bias largely explains the absolute PET error, so the analysis focuses on heat-stress classes and relative differences rather than exact point values. Wind and MRT were not measured; therefore, matching air temperature, humidity, and surface temperature is necessary but not sufficient for PET accuracy. Validating MRT with a globe thermometer remains a priority.

- Air temperature T_a (transect): pedestrian-height T_a along the photo walk route is compared with CFD $z=1.1$ m air temperature at route samples (scatter, RMSE/MBE/r), separating day and night.
- Relative humidity RH (transect): RH along the same route (CFD specific humidity converted to RH) is compared, checking the validity of ET and the humidity balance.
- Surface temperature T_s (44 points): the 44 contact-point surface temperatures are compared with CFD surface temperature. However, because the CFD lacks canopy radiative shading, it overestimates surface temperature at points directly beneath the canopy. The T_s validation is stratified by sun-dominated points, and the deviation at tree-shade points is reported separately as a systematic error relative to the uncoupled shade (validity is not claimed from a single lumped RMSE across all points).

Times are synchronized in UTC. A published URANS urban-microclimate validation shows mean absolute differences of about 2 °C for surface temperature and around 1.3 °C for air temperature (Antoniou et al., 2019; Chen et al., 2025), which we use as a reference. Since MRT and wind speed were not directly measured, PET is expressed within Matzarakis's heat-stress classes rather than as a precise point estimate to avoid overstating confidence.

Figure 6. CFD validation against the same-day field campaign. Left: pedestrian air temperature along the mobile transects, colored by local time. Right: surface temperature, with ground from the FLIR thermal camera (N=33) and sunlit and shaded walls from the contact sensor (N=10, 11); sunlit facades match within -0.4 °C while shaded facades and ground run cooler. 1:1 line dashed.



Source: this study.

4.3 Surrogate vs CFD holdout (leakage-free evaluation)

We assess surrogate accuracy using holdout data. To prevent information leakage from nearby points, which can cause R^2 to be overestimated due to spatial autocorrelation, the main evaluation metric uses a block holdout that divides the AOI into quadrants and excludes absolute coordinates (x, y) from features. The key operation, spatial downscaling or interpolation under specific weather conditions like air temperature, wind speed, and solar radiation, is tested with both block holdout and random holdout. We also include a time holdout that excludes peak hours as an extrapolation stress test for unseen forcing. Evaluation metrics include scatter plots,

R^2 , RMSE, and a spatial error map of the holdout PET. The speed ratio compares the wall-clock time per CFD time step plus shade post-processing to the surrogate inference time on the same hardware. Since configurations with occlusion features (*beam_DNI*, *SVF*) partly replicate the analytic relation used in training data, an ablation without these features, using only coarse inputs, is also presented to isolate the model's learning contribution.

5. Results

The results answer four key questions: when and where pedestrian PET enters the danger zone, the magnitude of the shading lever, how these levers compare, especially if reflective pavement is actually counterproductive, and whether the field can be quickly replicated. The data derive from paired vegetated and unvegetated runs with shade-aware post-processing. Absolute PET includes the +2.3 °C daytime air bias, so the main conclusions focus on heat-stress classes and differences between the levers.

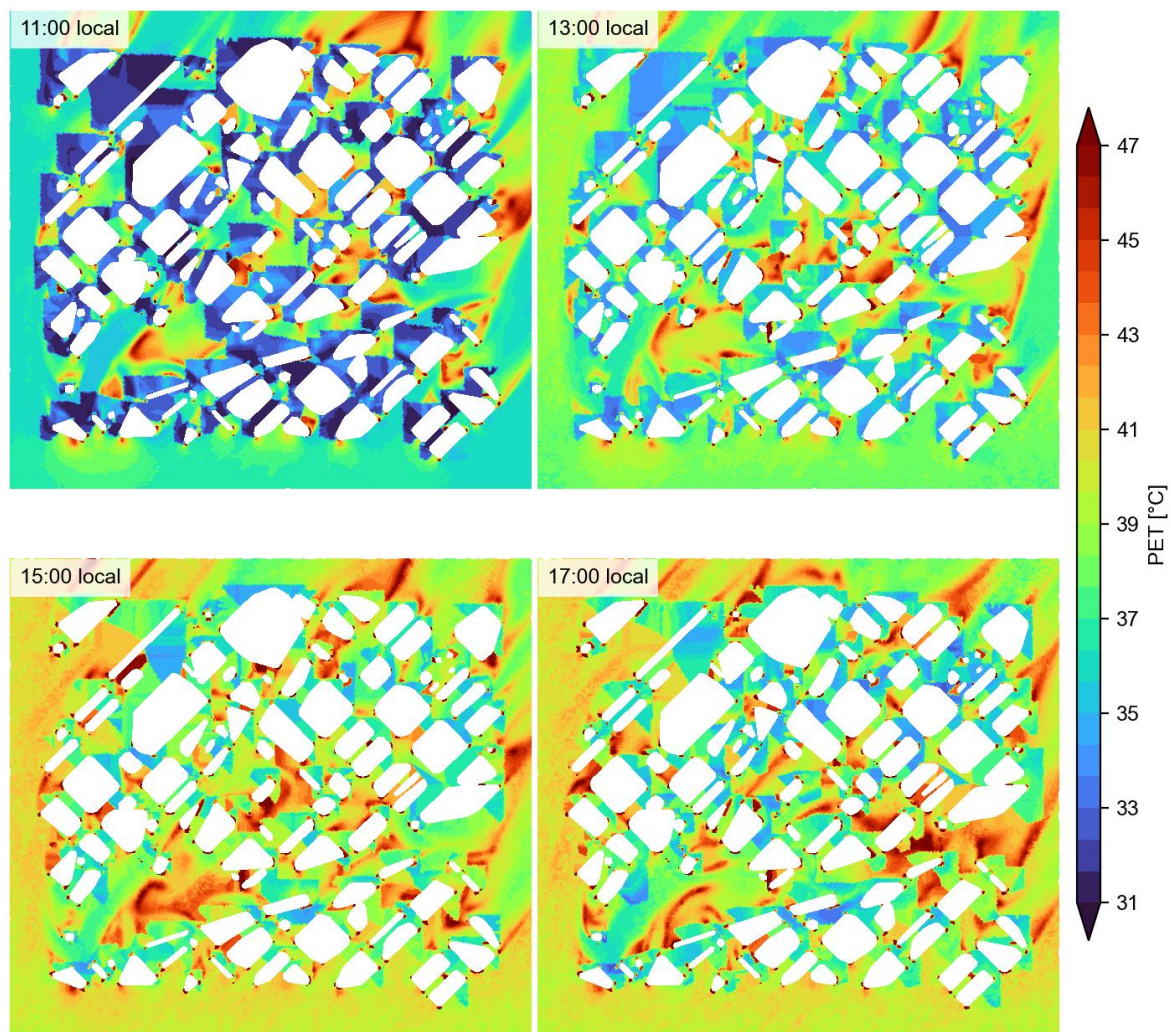
5.1 Diurnal PET and hotspots

Pedestrian-level ($z=1.1$ m) PET shows a distinct daily cycle over 24 hours (Fig. 7, Fig. 8). Average PET in the AOI is around 19 °C before dawn, rises past 35 °C into strong heat stress around 10:30 local as the canyons become sunlit, holds a broad afternoon plateau peaking at 40.1 °C near 15:50, drops below the strong threshold by about 19:00, and settles near 21 °C overnight. These absolute values carry a validated +2.3 °C daytime canyon-air bias, about +3.5 °C at midday, which we subtract in what follows. After the correction, the afternoon-peak AOI-mean is 34.7 to 36.5 °C, in the strong class; 40 to 78% of the pedestrian area is strong-or-extreme and 2 to 4% is extreme, and only shaded areas stay below the strong threshold. The 10th to 90th percentile spread is 5 to 6 °C, set by direct-beam exposure: unshaded east-west canyons, chamfered corners, and wide paved openings are hottest, while building shadows and some canopies cut PET locally. The block is dangerous at the pedestrian level nearly everywhere by mid-afternoon.

5.2 Cooling-pathway decomposition

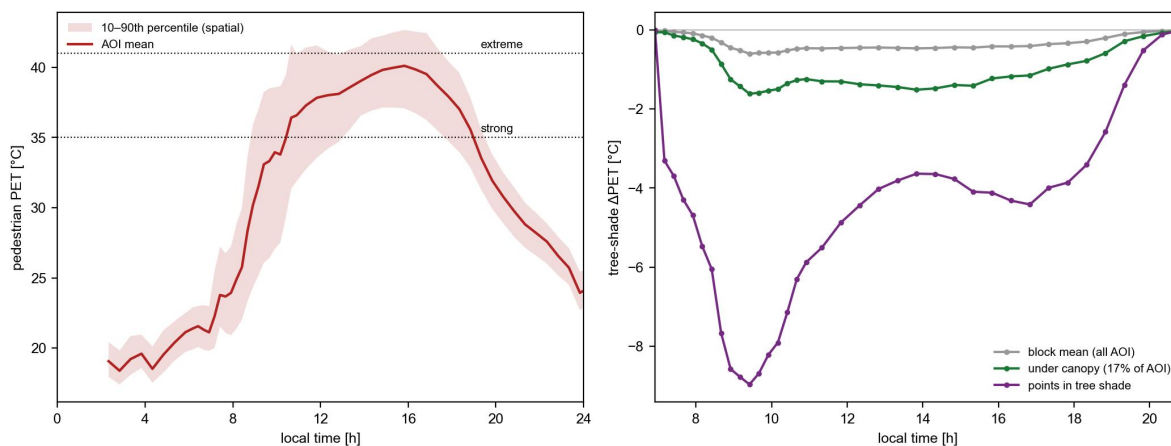
Dividing the street-tree effect into its three pathways clarifies which one is most significant (Fig. 9). During midday, the overall tree effect is -0.45 °C in AOI-mean PET, mainly due to shade: geometric canopy shading accounts for -0.44 °C, while evapotranspiration and canopy drag (wind) contribute only -0.01 °C. Their combined effect falls within the variation seen between vegetated and unvegetated scenarios. Although the block-mean effect looks small, it is diluted: canopy sits over 16.7% of the AOI and, at the afternoon peak, shades only 6 to 11% of it. Where a tree shades a pedestrian, the cooling is large. Points under canopy average about -1.2 °C, and points in tree shade average about -4 °C, reaching -9 °C locally (Fig. 8). Trees cool the pedestrian where and when their shadow falls, not across the block. This finding, supported by the coupled vegetation run, indicates that street-tree cooling on clear days mainly operates through MRT (shade) rather than air temperature, aligning with radiation-focused studies (Lachapelle et al., 2023; Yang et al., 2025). The near-zero evapotranspiration plus wind effect results from two opposing factors, transpiration cooling and reduced canyon ventilation due to canopy drag, that nearly offset each other in the overall block mean. This near-cancellation is a block-mean, clear-day result under a prescribed well-watered transpiration rate; it does not mean ET is locally negligible, and a drier day or a different irrigation regime would shift the balance.

Figure 7. Shade-aware pedestrian PET over the block at 11:00, 13:00, 15:00, and 17:00 local (CFD wind); buildings are voids, shared color scale. Absolute values carry the +2.3 °C canyon-air bias.



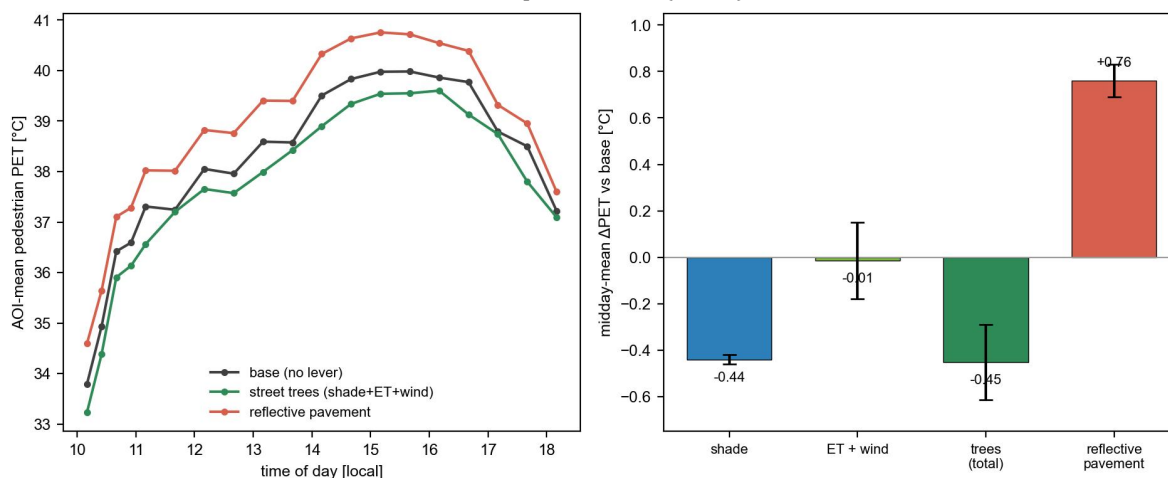
Source: this study.

Figure 8. Left: 24 h AOI-mean pedestrian PET with its 10-90th spatial percentile band (local time). Right: tree-shade cooling through the day for the whole block, for points under canopy (17% of the AOI), and for points in tree shade. The block mean stays small because the canopy is sparse and midday shadows are short, yet where a tree shades a pedestrian, the cooling reaches several degrees.



Source: this study.

Figure 9. Cooling-pathway decomposition and policy levers: AOI-mean PET for base, street trees, and reflective pavement (left); midday-mean dPET by pathway (right; error bars = spread across midday hours). Tree cooling is almost all shade ($-0.44\text{ }^{\circ}\text{C}$); ET+wind is negligible (-0.01); reflective pavement warms pedestrians ($+0.76$).



Source: this study.

5.3 Policy-lever comparison

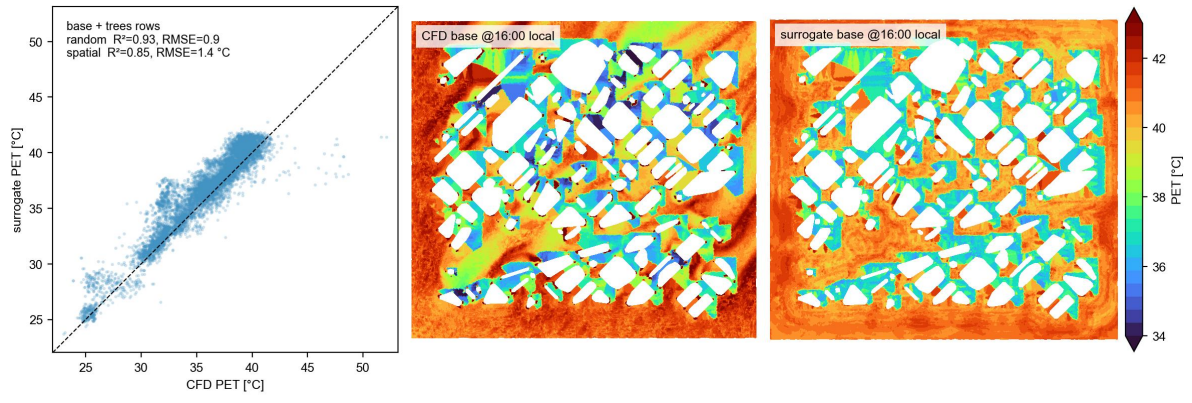
Comparing base, street trees, and reflective pavement on one PET metric separates measures that help pedestrians from measures that do not (Fig. 9). Raising ground albedo from 0.30 to 0.55 lowers the road-surface temperature but raises AOI-mean pedestrian PET by about $+0.76\text{ }^{\circ}\text{C}$ at midday, the only lever with a positive dPET, because the extra reflected shortwave reaches the body. This counts only the added shortwave: the radiant longwave term is approximated by air temperature, so it omits the smaller offsetting longwave cooling from the now-cooler pavement, and $+0.76\text{ }^{\circ}\text{C}$ is an upper bound on the net warming, whose sign is robust because the shortwave gain exceeds that offset. The sign is the message: a measure judged on surface temperature can worsen the pedestrian experience it is meant to improve. Between-lever differences are more dependable than absolute PET, since the shared canyon-air bias cancels in the difference. This bears directly on the city's reflective-pavement pilot and echoes standing concerns about high-albedo materials at pedestrian level (Erell et al., 2014; Schneider et al., 2023).

5.4 Surrogate performance and interpretation

The surrogate's evaluation simulates real-world use by predicting the block-scale pedestrian PET field at a specified time, given coarse weather forcing. It was trained using combined vegetated and unvegetated runs, using a scenario flag to choose the field type. The model achieved an R^2 of 0.93 (RMSE 0.9°C) on a random holdout, and 0.85 (RMSE 1.4°C) on a spatial-quadrant holdout that excludes absolute x/y features, making it a rigorous spatial test (Fig. 10, left). Inference is very fast, returning all block points and 30-minute steps within seconds, about a thousand times faster than the CFD-plus-shade chain. The maps (Fig. 10, middle and right) illustrate the metrics: the surrogate accurately reproduces the sun/shade patterns, with shaded canyons and sunlit areas correctly placed (peak-map spatial correlation 0.83). It smooths the sharpest extremes lightly (spatial std deviation 1.78°C vs CFD's 2.10). A component ablation clarifies the mechanism (Fig. 11): predicting air temperature, mean radiant temperature, wind, and humidity separately and combining them via the energy balance allows near-perfect reconstruction of the radiant field (R^2 0.99) and good predictions for temperature and humidity (R^2 0.85 and 0.90). Wind prediction is poor (R^2 below zero) because canyon wind is advective and depends on more than point geometry, so we map PET using a reference wind. Future work will develop a wind-resolved surrogate. Permutation importance shows *beam_DNI*, *build_dist*,

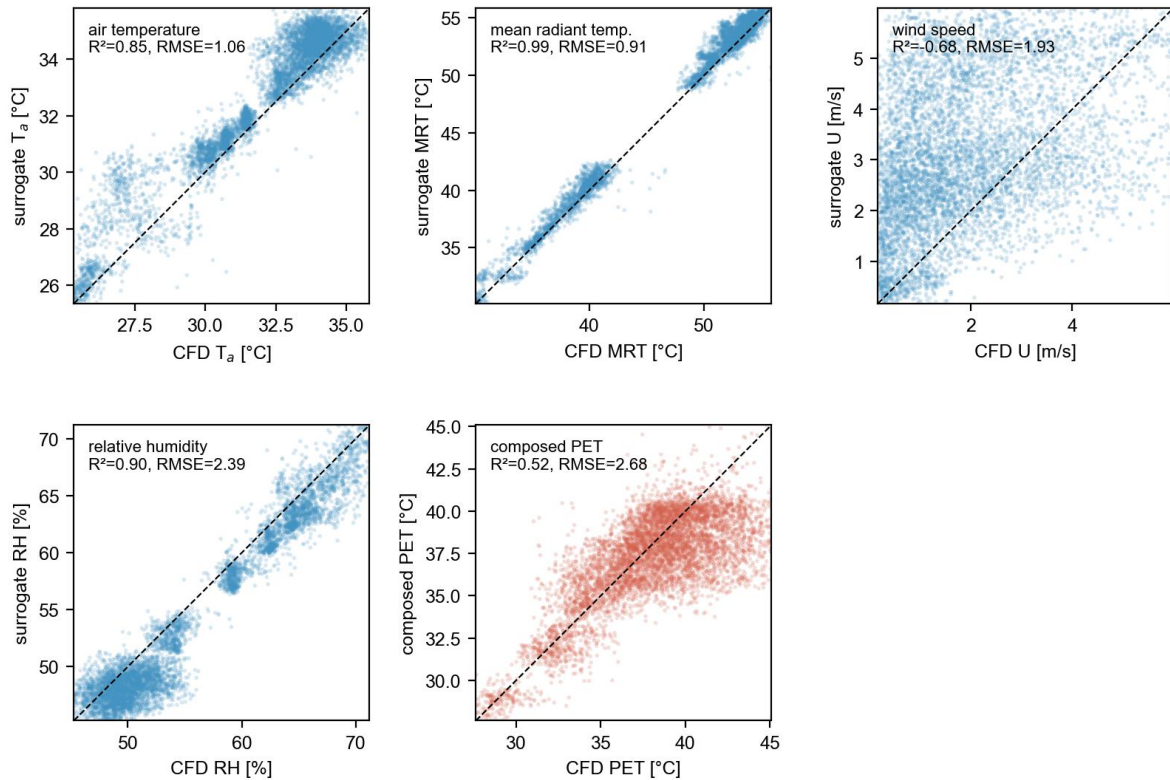
and sky-view factor as top features, aligning with physics that radiation and shading primarily drive clear-day PET (Alinasab et al., 2025; Cui et al., 2025). Since these occlusion features influence the training PET post-processing, an ablation isolates the model's contribution. Removing the analytic occlusion features (SVF, the beam-reach factor, and the derived radiative fluxes) that also enter the training PET lowers the spatial-holdout R^2 from 0.85 to 0.64 (random 0.93 to 0.76), and dropping all local geometry leaves 0.48; independent geometry proxies (building and canopy distance) therefore carry real spatial skill above the forcing-only floor, while the occlusion features supply the remainder.

Figure 10. Machine-learning surrogate versus CFD for reference-wind pedestrian PET, trained on the vegetated and unvegetated runs together: leakage-free holdout scatter (left) and base-case PET fields at the daytime peak on the true block mesh, shared scale (middle CFD, right surrogate). The surrogate places the shaded canyons and sunlit openings correctly and lightly smooths the sharpest extremes.



source: this study.

Figure 11. Component ablation: predicting air temperature, mean radiant temperature, wind, and relative humidity separately on the spatial holdout (top) and composing PET via the energy balance (bottom). The radiant and thermodynamic fields are reconstructed well (MRT $R^2=0.99$, RH 0.90, T_a 0.85); local wind is the only poorly predicted field ($R^2<0$), so PET is mapped at a reference wind.



Source: this study.

5.5 Quantitative comparison with prior work

Compared to previous studies, the figures match the method's predictions. Reported tree dPET in the literature reaches 12–16°C under dense, irrigated canopies with evapotranspiration (Teshnehdel et al., 2020; Zeeshan et al., 2022). The isolated shading pathway, geometric, block-averaged, and excluding ET, is smaller, amounting to a few kelvin locally and -0.44°C on average in the AOI. This represents a lower bound on total tree cooling, not an estimate. The surrogate's spatial interpolation, with an R^2 of 0.85 (and 0.93 for random data) from a single day, aligns with the ~ 0.9 R^2 of microclimate surrogates trained across many scenarios (Zhao et al., 2024; Javanroodi et al., 2022; Briegel et al., 2025). This performance is achieved here on one day by targeting the reference-wind PET, which coarse features can determine. Extrapolation to unseen forcing remains limited, consistent with other domain transfer limits (Wang et al., 2025). The contribution is not introducing a new absolute cooling number but providing a measurement-verified, meter-scale PET field that is reproducible and quick, enabling a shading-versus-pavement decision for a specific street and hour.

6. Discussion

6.1 Positioning within the literature

We put trees, reflective pavement, and shelter access on one pedestrian-PET field for a real superblock, checked against a same-day campaign. Their effects, including opposite signs, can then be compared directly and matched to the measures the city is building. The shading outcome emphasizes radiation-focused work, where street-tree cooling mainly occurs through MRT with minimal air-temperature impact (Lachapelle et al., 2023; Yang et al., 2025). While many ENVI-met studies report only a net dPET (Teshnehdel et al., 2020; Detommaso et al., 2021), this research breaks down the overall effect into shade, evapotranspiration, and wind effects in PET units, linking each to specific policy options. It directly highlights the reflective pavement trade-off: high-albedo pavement cools the road but can increase pedestrian PET (Errell et al., 2014; Schneider et al., 2023; Mohammad et al., 2021). The vegetated model explicitly accounts for evapotranspiration and canopy drag, finding them negligible on a clear day for the block average, with shade (MRT) providing most benefit, aligning with Lachapelle et al. (2023). Compared to CFD models that achieve $R^2 \sim 0.9$ by training on numerous cases (Caron et al., 2025; Mao et al., 2025; Zhao et al., 2024), this study emphasizes the training source, high-fidelity Fluent-RANS with shade post-processing, validated against field data, rather than just accuracy. SHAP analysis shows radiation and shading features as the most influential, supporting evidence that radiation impacts outdoor comfort more than morphology (Alinasab et al., 2025; Cui et al., 2025).

6.2 Path to generalization

This study presents a concept for a single block on a clear day, without claiming applicability across entire cities or in all weather conditions. Its main limitations are due to this focus: shade was calculated separately rather than incorporated into the CFD model, leading the opaque-canopy assumption to overestimate shade cooling, while the absence of air-temperature feedback results in underestimation, making the overall effect uncertain. Since MRT and wind speed were not measured, the comparison of air temperature, relative humidity, and surface temperature offers necessary but limited validation. PET results are shown in heat-stress categories and differences (dPET) between levels, rather than precise point values. Additionally, uncertainties come from the mean-field Reynolds-averaged (RANS) closure, wall-function convective transfer, Boussinesq reference temperature, prescribed transpiration, and the single-day, single-block training.

Each limitation has a straightforward fix. Incorporating multi-day, multi-block CFD into the training data would enable the surrogate to predict beyond known morphologies and weather conditions. Implementing stable canopy-radiation coupling would incorporate shading effects

into the CFD and capture their impact on air-temperature feedback. Measurements of globe temperature and wind would directly validate MRT and PET. Embedding the surrogate into a rapid optimization loop that explores different design options (such as species, layout, and pavement) would turn it into a planning aid through a reduced-order model (ROM). A sensitivity sweep over canopy transmittance, surface albedo, and leaf-area density would bound the parameter uncertainty.

Pedestrian wind is the one field the point-feature surrogate does not reconstruct (spatial R^2 below zero in the component ablation), because canyon wind is an advective, non-local function of the upstream layout rather than of the local sky-view factor or building distance. Coupling a layout-reading wind branch (Javanroodi et al., 2022) to the present surrogate is the route to a wind-resolved PET field. Here, PET is mapped at a reference wind, and the wind sensitivity is reported separately, the honest scope given that wind was not measured.

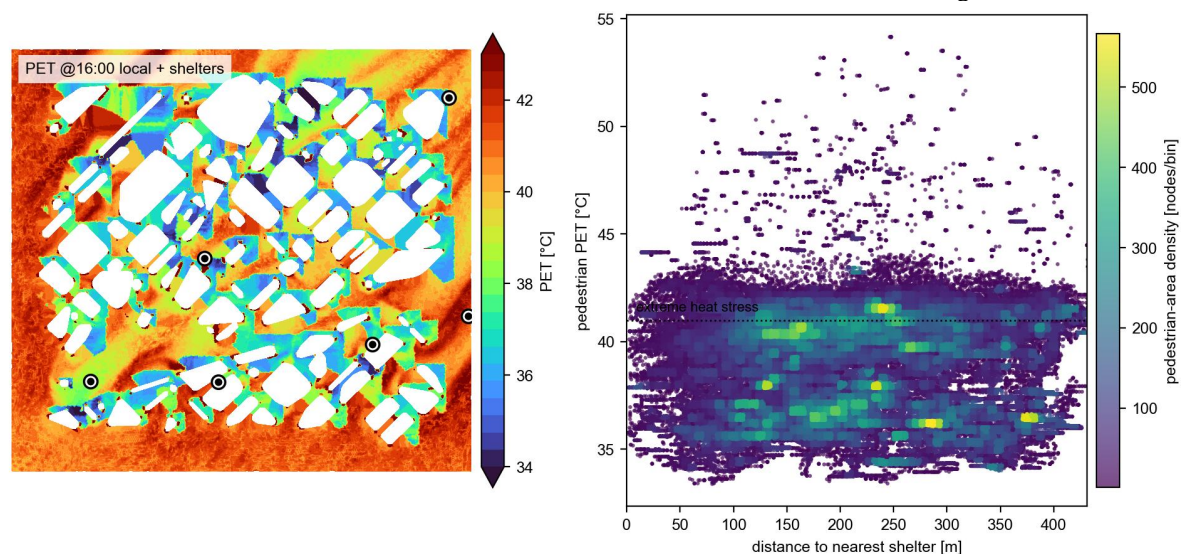
6.3 Implications for street trees, reflective pavement, and shelters

Street-tree cooling at the pedestrian level is primarily shade, determined mainly by the location and timing of canopy coverage. Measure selection is therefore purpose-driven: dense, strategically placed canopy where shade matters most, and irrigation systems where transpiration is essential. For the Pla director de l'arbrat (canopy increasing from 25.2% to 30%), this argues for prioritizing beam-blocking canopy on the hottest streets over uniform coverage targets.

Reflective pavement can lower surface temperature but may increase pedestrian PET by about $+0.76$ °C at midday, because reflected radiation reaches the body, the only lever with a positive dPET, and an upper bound because the estimate omits the offsetting longwave cooling of the cooler surface. High-albedo materials should therefore be used only sparingly on pedestrian streets, echoing standing concerns at pedestrian level (Erell et al., 2014; Schneider et al., 2023), and the city's reflective-pavement pilot should be assessed on pedestrian PET rather than surface temperature.

For the cool-shelter network (about 500 shelters in summer, with 98% of residents within a 10-minute walk), the approach shifts focus from area-based metrics such as shelter accessibility to street-level decision-making: a detailed map highlights pedestrian PET hotspots and identifies the most cost-effective interventions to reduce them (Fig. 12). It also supports shaded routes to shelters, so the walk itself cools rather than just counting them.

Figure 12. Access to climate shelters: afternoon-peak pedestrian PET overlaid with Barcelona's refugis climàtics network within a walkable buffer, and distance to the nearest shelter against local PET.



Source: this study, Open Data BCN.

7. Conclusions and policy implications

This study calculated pedestrian PET for a real Barcelona superblock at meter resolution over an entire day, validated it with field data, and broke down street-tree cooling into shade, evapotranspiration, and wind components. It compared policy levers using a single PET metric and replicated the field results with a machine-learning surrogate at roughly 1,000 times less computational cost. Across the levers, differences in PET (dPET) proved more reliable than absolute PET because shared biases cancel out, making attribution and ranking more trustworthy.

Overall, the work shows that detailed urban microclimate physics can be calculated rapidly enough for planning. The surrogate returns the meter-scale PET field in seconds, so planners can map any hour of the block's day without rerunning the CFD. The physics-based attribution also keeps each comparison clear and understandable. The superblock-scale PET model could be readily extended to Barcelona's other superblocks and to other cities that adopt the superblock model. Including more days, blocks, and directly validating radiant temperature in the training data would turn this proof of concept into a usable reduced-order model for heat-resistant street design.

8. Acknowledgments

During the preparation of this manuscript, the authors used a generative AI assistant (Anthropic Claude) to help draft and edit the text, and to write and debug the analysis and visualization code (data processing, the shade-aware PET post-processing, the machine-learning surrogate, and the figures) working from the authors' own simulation output and field measurements. The AI was not used to generate, fabricate, or alter scientific data or results. The authors designed the study, ran the CFD simulations and the field campaign, and reviewed and verified all code, figures, analysis, interpretations, and conclusions, for which they take full responsibility.

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