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WRF-Comfort: Simulating micro-scale variability of outdoor heat stress at the city scale with a mesoscale model

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Abstract. Urban overheating, and its ongoing exacerbation due to global warming and urban development, leads to increased exposure to urban heat and increased thermal discomfort and heat stress. To quantify thermal stress, specific indices have been proposed that depend on air temperature, mean radiant temperature (MRT), wind speed, and relative humidity. While temperature and humidity vary on scales of hundreds of meters, MRT and wind speed are strongly affected by individual buildings and trees, and vary at the meter scale. Therefore, most numerical thermal comfort studies apply micro-scale models to limited spatial domains (commonly representing urban neighborhoods with building blocks) with resolutions on the order of 1 m and a few hours of simulation. This prevents the analysis of the impact of city-scale adaptation/mitigation strategies on thermal stress and comfort. To solve this problem, we develop a methodology to estimate thermal stress indicators and their subgrid variability in mesoscale models - here applied to the multilayer urban canopy parametrization BEP-BEM within the WRF model. The new scheme (consisting of three main steps) can readily assess intra-neighborhood scale heat stress distributions across whole cities and for time scales of minutes to years. The first key component of the approach is the estimation of MRT in several locations within streets for different street orientations. Second, mean wind speed, and its subgrid variability, are parameterized as a function of the local urban morphology based on relations derived from a set of microscale LES and RANS simulations across a wide range of realistic and idealized urban morphologies. Lastly, we compute the distributions of two thermal stress indices for each grid square combining all the subgrid values of MRT, wind speed, air temperature, and absolute humidity. From these distributions, we quantify the high and low tails of the heat stress distribution in each grid square across the city, representing the thermal diversity experienced in street canyons. In this contribution, we present the core methodology as well as simulation results for Madrid (Spain), which illustrate strong differences between heat stress indices and common heat metrics like air or surface temperature, both across the city and over the diurnal cycle.

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1 Introduction

The combination of urban development and climate change has increased heat exposure in cities in recent decades (Tuholske et al., 2021) and a continuation of these trends in the 21st century would be difficult to offset locally from an air temperature perspective (Broadbent et al., 2020; Krayenhoff et al., 2018; Zhao et al., 2021). Adaptation options that target contributions to heat exposure other than the air temperature, such as radiation (e.g., via shade) and wind (e.g. via improved street ventilation), should therefore be considered. Quantification of these contributions relative to air temperature requires the application of comprehensive thermo-physiological heat stress metrics such as the Universal Thermal Climate Index, UTCI (Jendritzky et al., 2012), the Physiological Equivalent Temperature, PET (Höppe, 1999), or the Standard Effective Temperature, SET (Gagge et al., 1986). Moreover, exposure to heat hazards is moderated by infrastructure-based and social/mobility-based adaptations to heat, and by buildings and associated cooling mechanisms. Here, the focus is the development of a tool to quantify the outdoor component of heat exposure in cities, accounting for all relevant meteorological variables.

Heat exposure in urban areas is affected by several meteorological variables that vary on different spatial and temporal scales (Nazarian et al., 2022). While temperature and humidity vary on spatial scales on the order of hundreds of meters, shortwave and longwave radiation and wind speed are strongly affected by individual buildings and vary at the scale of a few meters. For this reason, most numerical thermal comfort studies in urban areas apply micro-scale models with resolutions on the order of 1 m and spatial domains that are limited to an urban block or neighborhood (Nazarian et al., 2017; Zhang et al., 2022; Geletič et al., 2018). While these studies include substantial detail at the micro-scale, they are very expensive computationally and therefore can be applied only to a few neighborhoods and they neglect the interactions with larger scale meteorological phenomena (e.g., land/sea breezes, mountain/valley winds, urban breezes) that often play a relevant role in outdoor thermal comfort and its variation across cities. On the other hand, contemporary meso-scale numerical models can be applied to the whole urban area and surrounding regions, and therefore capture these larger-scale phenomena, but have spatial resolutions of several hundred meters at best. These models use a grid mesh that does not resolve buildings and is therefore too coarse to capture the fine-scale variation of radiation and wind flow of relevance to outdoor heat exposure and ultimately thermal comfort.

The objective of this work is to fill the aforementioned gap by developing a model that includes the most crucial capabilities of micro-scale assessments of thermal exposure within meso-scale models. This new model will quantify the spatial variability (i.e., statistical representation of the microscale distribution) for longwave and shortwave radiation as well as wind speed within each meso-scale grid square. Subsequently, it will capture the range of thermal exposure, as quantified by the UTCI and SET thermal stress metrics, within each urban grid square across a city at each time of day. The focus here is on the *range* of thermal exposure, such that we identify the cool and hot spots within the grid cell without having to resolve the entire spatial distribution. We argue that this represents the most crucial information for heat management and urban design interventions, as it identifies whether people can move and search for optimal thermal conditions. For example, if hot

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spots are experiencing extreme heat stress but the cool spots are at slight heat stress, pedestrians have the opportunity, and autonomy, to seek shade and thermal respite (i.e., spatial autonomy as described in Nazarian et al. (2019)). Conversely, if the conditions in the cool spot are already in extreme heat stress, this can be used to inform urban design interventions or heat advisories to vulnerable populations to avoid being outside at that place and time. Overall, representing the range of heat exposure at the neighborhood scale while covering regional-scale phenomena is key to human-centric assessments of urban overheating (Nazarian et al., 2022).

The new model is embedded in the multi-layer urban canopy parameterization BEP-BEM (Martilli et al., 2002; Salamanca et al., 2010) which simulates the local-scale meteorological effects of the grid average urban morphology within the Weather Research and Forecasting (WRF) mesoscale model (Skamarock et al., 2019 version 4.3 has been used in this study). Here, BEP-BEM is extended to quantify the spatial variation of the mean radiant temperature and wind speed within the grid square at the pedestrian level. To our knowledge, three schemes in the published literature have attempted to capture thermal exposure in an urban canopy model. Pigliautile (2020) implemented a scheme to estimate human thermal exposure in the Princeton Single-Layer Urban Canopy Model. However, the scheme has not been run within a mesoscale model. Jin et al. (2022) calculate urban mean radiant temperature (MRT) in a mesoscale model, while Lemonsu (2015) and Leroyer et al. (2018) assess UTCI in mesoscale modeling applications within Paris and Toronto, respectively. Moreover, Giannaros et al (2018, 2023), made an offline coupling of WRF-BEP_BEM with RayMan (Matzarakis et al. 2007). However, none of these approaches account for the within-grid spatial variation of wind speed, and their assessment of sub-grid spatial variation of radiation exposure (i.e., mean radiant temperature) is limited. Here, we further extend the BEP-BEM model embedded in the WRF meso-scale model to overcome these limitations and more fully assess spatial variation of thermal exposure within each urban grid square.

In section 2, the methodology is described in detail, with a focus on model development and implementation in WRF. In Section 3, we present an example of the type of outputs that can be produced. Conclusions are in section 4.

2 Methodology

The most complete thermal stress indices invariably depend on four meteorological variables: air temperature, mean radiant temperature (MRT), relative humidity, and wind speed. Among these, MRT and wind speed have the largest spatial variability in the urban canopy, and this variability is often captured with 3D micro-scale models of urban airflow and radiative heat transfer. At the meso-scale, however, it is not feasible to incorporate such models, motivating the simplified urban canopy parameterizations developed here. Below we detail how the BEP-BEM urban canopy model is modified to a) introduce a simplified model for MRT variation within a meso-scale grid cell (Sec. 2.1) and b) parameterize airflow variability (Sec. 2.2) in the urban canopy within a grid cell, and make a simple estimate of air temperature variability. These meteorological parameters are then used to estimate the sub-grid scale variation of thermal stress indices (Sec. 2.3), namely

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SET and UTCI, as two of the most commonly used indices for outdoor environments (Potchter et al 2018). Lastly, we discuss how multi-scale temporal and spatial variabilities in thermal exposure can be effectively communicated using the outcomes of the updated WRF-BEP-BEM model.

2.1 A simplified model for MRT variability in the urban canopy

The mean radiant temperature is a measure of the total radiation flux absorbed by the human body, including both shortwave (from the sun, either directly or after reflection on the walls or road) and longwave (emitted from solid bodies like walls or road, or from the sky) radiation. Whether pedestrians are shaded or in the sunshine, as well as their distance from warm surfaces emitting radiation, is therefore very important. BEP-BEM applies a simple urban morphology: two street canyons of different orientations, each with the same street width and building height distribution on each side of the canyon (Martilli et al. 2002). To capture the within-grid spatial extremes of mean radiant temperature, we assess pedestrian locations at the center of the street for two canyon orientations considered in BEP-BEM and at positions located at a distance of 1.5 m from the building wall on each side of the street, representing the sidewalks. Thus, there are 6 positions (three for each street direction) in each urban grid square where we compute the mean radiant temperature (shown for the example of North-South and East-West streets in Fig. 1). For shortwave reflection and longwave emission and reflection, the standard BEP view factor and shading routines (Martilli et al. 2002) are used to estimate the amount of shortwave (direct and diffuse) and longwave radiation reaching a vertical segment 1.80 m tall and located in each of the six positions previously mentioned (Fig. 1). Reflection of shortwave radiation and emission and reflection of longwave radiation from both building walls and the street surface are accounted for via these view factors. The pedestrian is "transparent" from the perspective of the urban facets, meaning that its presence does not alter the shortwave and longwave radiation reaching the building walls and road. The mean radiant temperature is computed by weighting the radiation reaching each side of the vertical segment by 0.44, and the radiation reaching the downward- and upward-facing (at 1.80 m height) surfaces of the pedestrian by 0.06 each. This approach follows the six-directional weighting method (Thorsson et al. 2007) and aggregates the four lateral weightings of 0.22 into two lateral weightings of 0.44 since BEP-BEM is a two-dimensional model (e. g. the streets are considered infinitely long). Namely,

$$T_{MRT} = \sqrt[4]{\frac{\sum_{i=1,4} W_i (a_K K_i + a_L L_i)}{a_L \sigma}} \qquad (1)$$

where, for an N-S oriented street, i=1,2 are for the vertical sides of the pedestrian looking East, and West respectively, and i=3,4 are for the top and bottom. Therefore, $W_{1,2}$=0.44, while $W_{3,4}$=0.06, a_K=0.7, and a_L=0.97, $K_{1,2}$ and $L_{1,2}$ are the short and longwave radiation reaching the vertical segment, and $K_{3,4}$ and $L_{3,4}$ are short and longwave radiation reaching the top and bottom respectively, and σ is the Stefan-Boltzmann constant.

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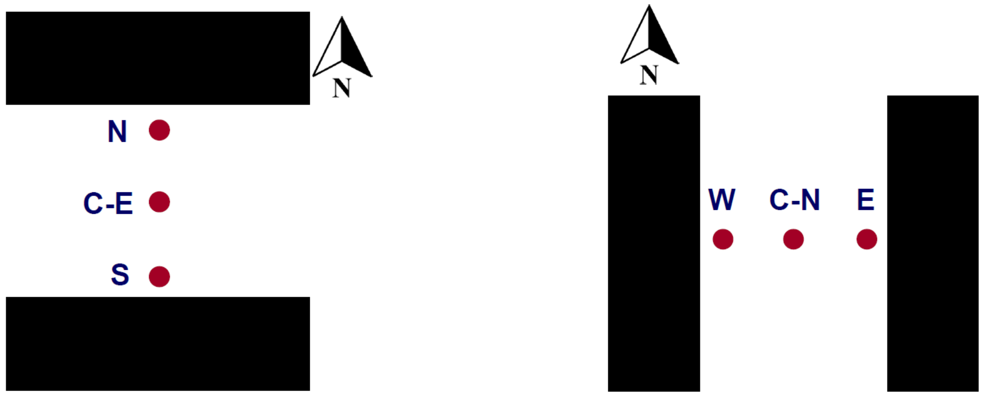

Figure 1: Two street directions (left: E-W canyon, right: N-S canyon) and pedestrian locations considered for Mean Radiant Temperature calculations.

The diurnal progression of the mean radiant temperature computed by this new model in BEP-BEM is subsequently compared with that obtained from TUF-Pedestrian, a more detailed three-dimensional model that has been evaluated against measurements (Lachapelle et al. 2022). TUF-Pedestrian is configured with identical input parameters and meteorological forcing, and with long canyons that approximate the two-dimensional BEP-BEM canyon geometry. The new model clearly captures the relevant details of the diurnal progression of MRT at all six locations (Fig. 2), with a mean absolute difference of 3.4 K, and a root mean square difference of 4.3 K across all locations. A comparison of the shortwave radiation loading on the pedestrian between the two models reveals excellent agreement (Appendix A Fig. A1, A2); thus, most of the model disagreement arises from differences between longwave loading on the pedestrian as a result of different methods for computation of surface temperature between the models. Overall, the new model of mean radiation temperature in BEP-BEM provides satisfactory results.

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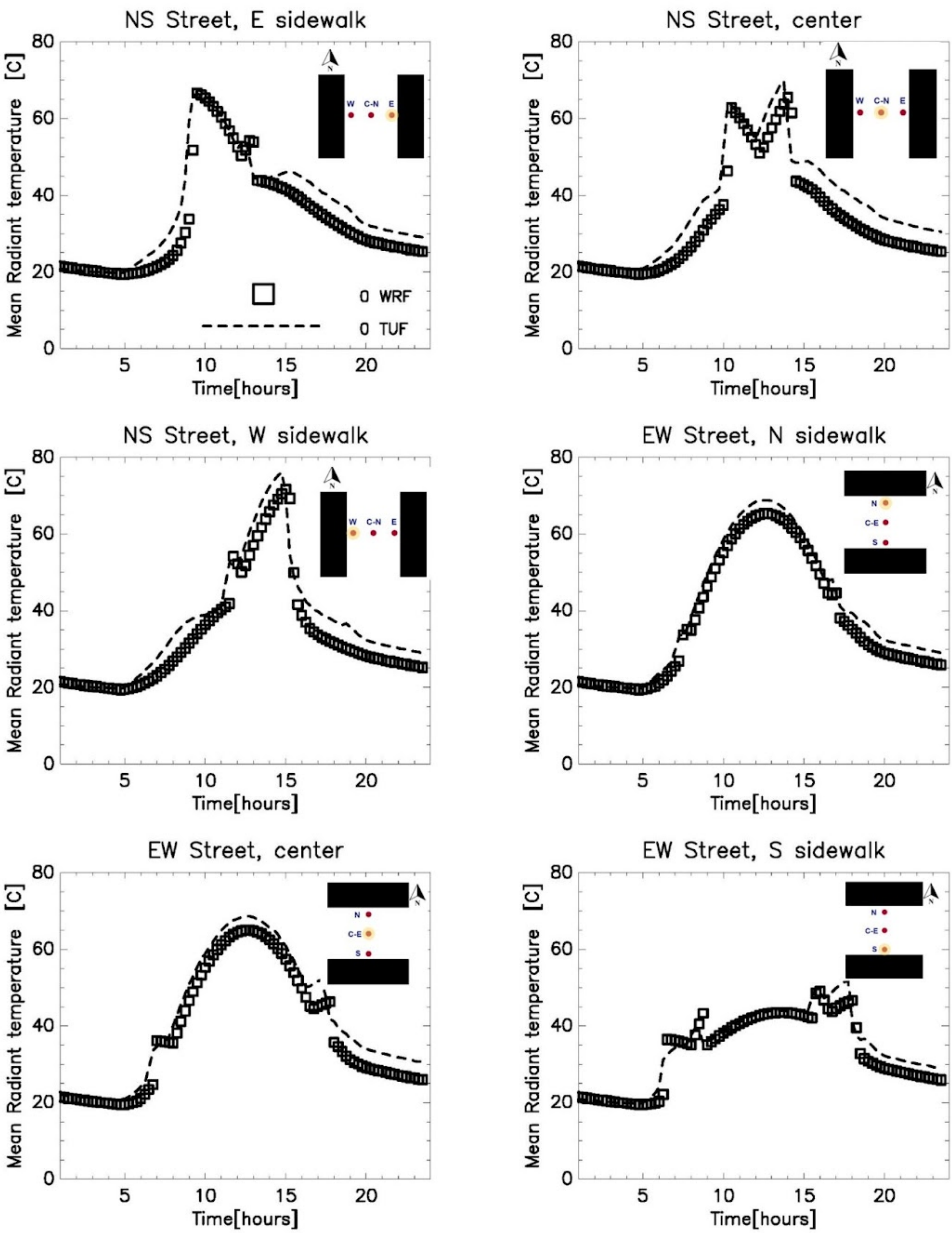

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Figure 2: Comparison of diurnal variation of Mean Radiant Temperature (MRT) between the new model in BEP-BEM and TUF-Pedestrian for each of the six locations in Fig. 1.

2.2 Parameterize airflow variability in the urban canopy

Mesoscale models solve conservation equations for the three components of momentum. From these, it is possible to derive the spatially averaged wind velocity in each grid cell, at the grid resolution of the mesoscale model, commonly of the order of 300m-1km. The spatially averaged wind velocity in the urban canopy $\langle V \rangle$, close to the pedestrian height (~2.5m), is the square root of the sum of the spatial average of the two horizontal components *u*, and *v*, (neglecting the vertical component, which is usually at least one or two orders of magnitude smaller than the horizontal),

$$\langle V \rangle = \frac{1}{Vair}\sqrt{\left(\int_{Vair} udV\right)^2 + \left(\int_{Vair} vdV\right)^2} \qquad (2)$$

where here *Vair* is the volume of the grid cell occupied by air (e. g. without the buildings)

However, the wind velocity calculated in mesoscale models is different from the average wind speed that would be experienced by a person in the grid cell. This is better represented by the spatial average of the wind speed $\langle U \rangle$ (e. g. the module of the vector), written as

$$\langle U \rangle = \frac{1}{Vair}\int_{Vair} \sqrt{u^2 + v^2}\,dV \qquad (3)$$

To assess the impact of airflow on human thermal comfort, the wind speed should be estimated from the wind velocity computed in the mesoscale models. Additionally, it is critical to parameterize and estimate the spatial variability of mean wind speed in the urban canopy. Accounting for these factors, the range of wind speed variability at the pedestrian level is estimated, which is critical for the quantification of spatial variability of outdoor thermal stress and comfort.

Here, we describe the parameterization of a) wind speed-to-velocity ratio and b) wind speed distribution, based on urban density parameters. Data from over 173 microscales CFD simulations of urban airflow are considered over realistic and idealized urban configurations, spanning a wide range of building plan area (λ_P), frontal area (λ_F), and wall area (λ_w) densities representative of realistic urban neighborhoods in different types of cities. CFD simulations are conducted using 162 large-eddy simulations (LES) and 11 Reynolds-averaged Navier–Stokes (RANS) schemes detailed in Appendix B.

Mean wind velocity $\langle V \rangle$, speed $\langle U \rangle$ and its spatial standard deviation (σ_U) are computed at a horizontal cross-section at pedestrian height for each CFD simulation and used for deriving parameterizations (Fig 3). An additional data point is added at $\lambda_P=\lambda_w=0$, ensuring that wind speed is equal to wind velocity, and its standard deviation is set to zero, for the non-urban case.

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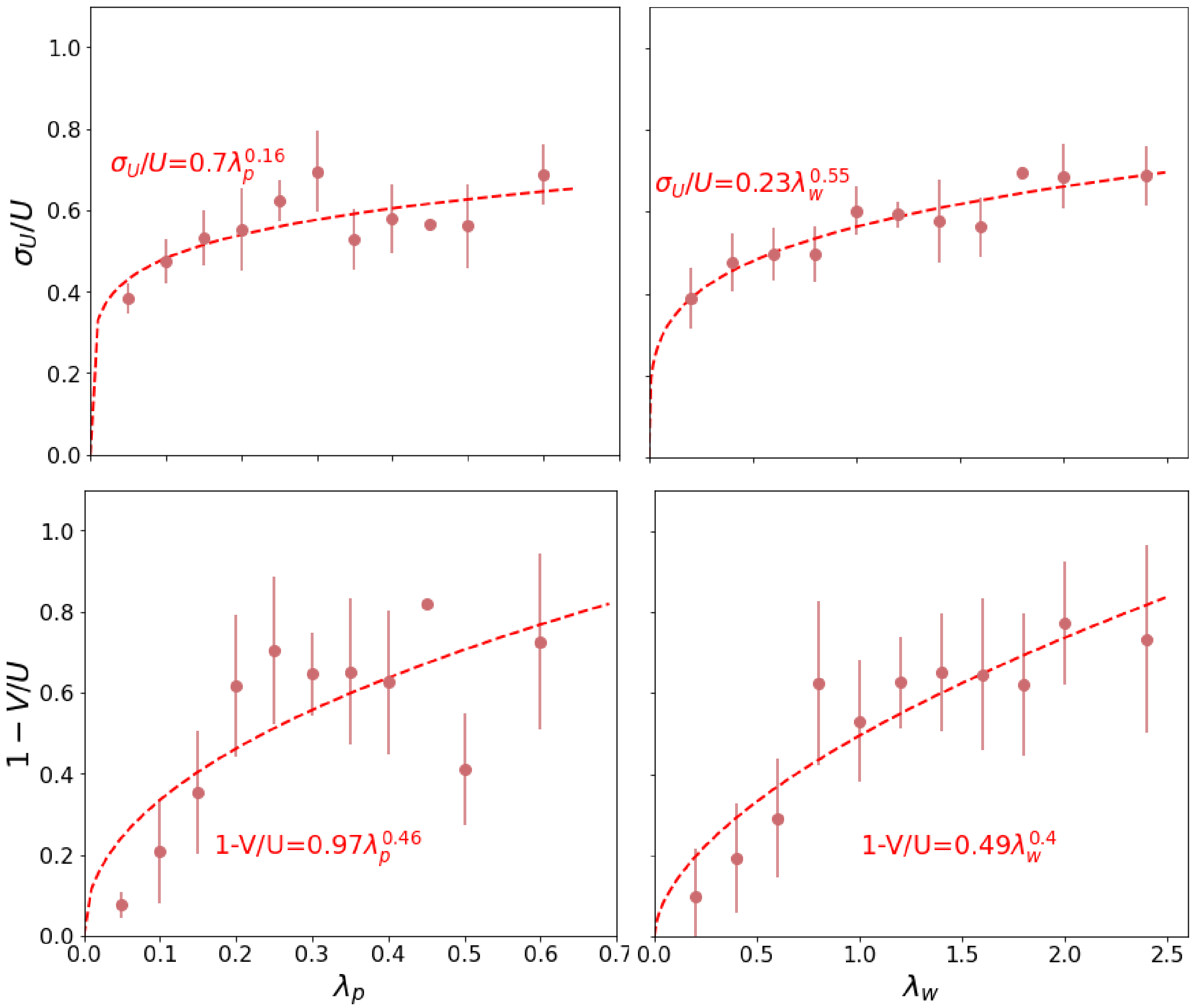

Figure 3: Relationship between 1-<V>/<U> (bottom row), and σ_U/<U> (top row), and two morphological parameters, λ_P (left column), and λ_W (right column) based on the CFD simulations. Dots represent the average of the value among all the simulations that share the same morphological parameter, and the vertical bar indicates the standard deviation. The dashed line and the formula indicate the best fit.

Parameterizations are derived (shown in Fig. 3) for two density parameters (λ_P=Ap/Atot, and λ_w=Aw/Atot, where Ap is the area of the horizontal surface occupied by buildings, or the roof area, Aw is the area of vertical (wall) surfaces, and Atot is the total horizontal area). We find that λ_w better predicts mean wind speed and its spatial variability at the pedestrian height, because it represents both horizontal and vertical heterogeneities in the urban canopy. Note that λ_F has not been included in

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the study, given the difficulty to estimate it for real urban areas, and to translate it to the simplified 2D urban morphology used by BEP-BEM. In any case, λ_F is closely related to λ_w. Therefore, the following parameterizations are implemented at the pedestrian height (1.8m) as a function of the wall area density λ_w

$$\langle U\rangle = \frac{\langle V\rangle}{1-0.49{\lambda_w}^{0.4}} \quad (4)$$

$$\sigma_U = \langle U\rangle(0.25{\lambda_w}^{0.55}) \quad (5)$$

We, therefore, assign three values of wind speed in each grid cell,

$$\langle speed\rangle_1 = max(0.01, \langle U\rangle(1 - 0.25{\lambda_w}^{0.55}))$$

$$\langle speed\rangle_2 = \langle U\rangle \quad (6)$$

$$\langle speed\rangle_3 = \langle U\rangle(1 + 0.25{\lambda_w}^{0.55})$$

Note that here we consider the three values equally likely, in order to realistically span the range of possible values that the wind speed can take in each grid cell. Since UTCI has been designed for 10m wind speeds, a simple log law is used to rescale wind speed at 10m, before passing it to the UTCI routine.

2.3 Calculation of the thermal comfort index

To represent the subgrid spatial variability of air temperature, detailed CFD simulations are not available, so we simply used a variability of 1 degree Celsius, which we consider to be a conservative estimate of the spatial variability of air temperature over a spatial scale of the order of one km squared. Therefore, for each grid cell, we have three values for air temperature:

$$Temp_1 = Temp_{WRF} - 1$$

$$Temp_2 = Temp_{WRF} \quad (7)$$

$$Temp_3 = Temp_{WRF} + 1$$

Where $Temp_{WRF}$ is the air temperature provided by WRF.

We therefore have, for each urban grid cell, *three* values of wind speed, *three* values of temperature, and *six* values of mean radiant temperature. No variability of the absolute humidity is considered, but the relative humidity is computed using the three values of air temperature.

Based on the variation of these climate variables, assumed uncorrelated, 54 possible combinations of the air temperature, mean radiant temperature, and wind speed values can be formed. For each one of these combinations, we calculate the corresponding SET or UTCI value. Based on the resulting distribution, we estimate the value of the 10th, 50th, and 90th percentile SET or UTCI for each grid square (at each output time).

3. Characterization of thermal comfort in regional-scale models: Madrid case

To illustrate the capabilities of the new scheme, a typical heat wave day in the city of Madrid (Spain) is simulated with WRF. Madrid is located on a plateau at 500-700m above sea level, in the middle of the Iberian Peninsula. It experiences hot summers, with frequent heat waves that are increasingly causing severe heat stress in the population, and it is therefore considered a relevant case study. Four nested domains have been used, with resolutions of 27,9,3, and 1km respectively. The city morphology (Fig. 4) is derived from high-resolution LIDAR data that covers most of the metropolitan area of Madrid (Martilli et al., 2022), while the morphology of the surrounding towns is determined based on Local Climate Zone maps (Brousse et al., 2016). It is also important to mention that the city is located on a hilly terrain, with higher elevations in the N-W part of the urban area (around 700m a.s.l.) dropping to 500m a.s.l. or less in the S-E. Moreover, there are two topographical depressions on the two sides of the city center, caused by the rivers Jarama and Manzanares (for a detailed description of the topography see also Martilli et al. 2022, where the same set-up was used). Other model configurations are the NOAH vegetation model for the non-urban grid points and the Bougeault and Lacarrere (1989) PBL scheme for turbulence parameterization. WRF coupled with BEP-BEM has previously been successfully used to simulate a heat wave period in Madrid (Salamanca et al., 2012). The period used in this paper is three days (14-16 July 2015). In particular, the analysis will focus on the 15th, when the maximum simulated temperature was above 40 Celsius. More information about the validation and a sensitivity study to select the optimal set-up can be found in Rodriguez-Sanchez (2020).

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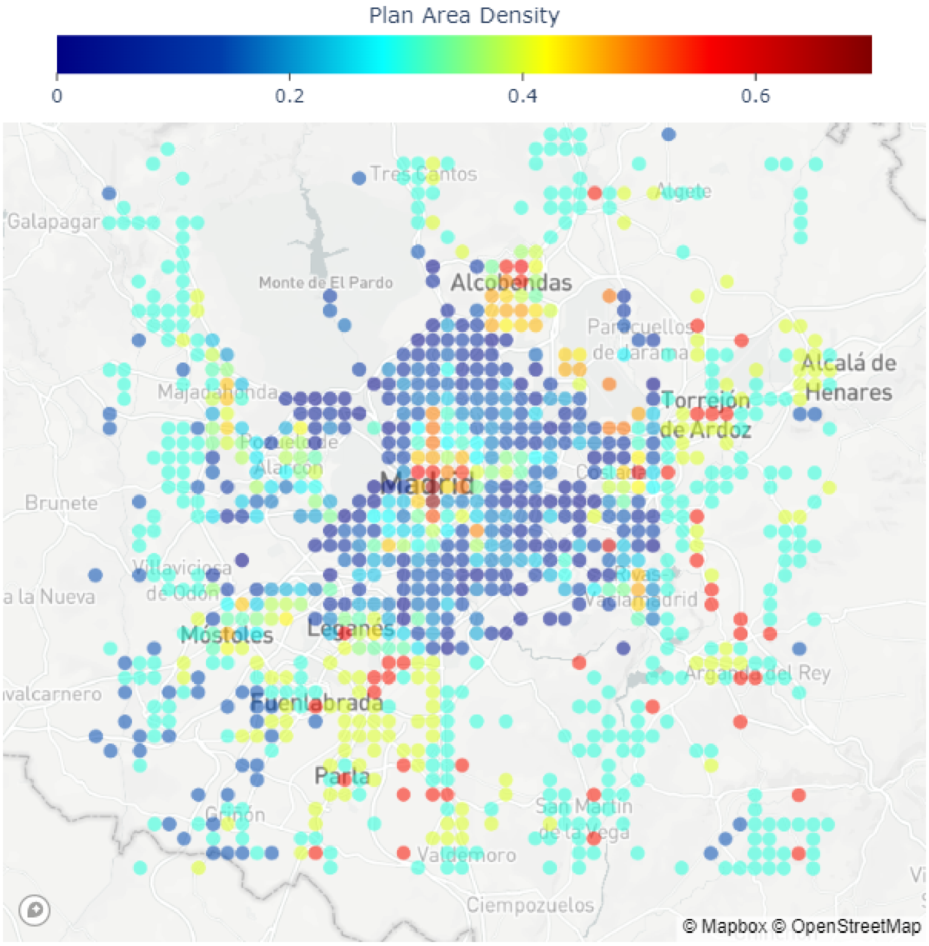

Figure 4. Map of the plan area building density over the Madrid region. The underlying map was created with Mapbox OpenStreetMap

3.1 Sub-grid scale variability of MRT and thermal comfort.

In order to understand how urban morphology affects the simulated heat stress, we focus on two grid points with very different urban morphology. One is located in the dense core of the city, with a building plan area density of λ_P =0.69, and a height-to-width ratio (H/W) value of 1.6. The second is located in the southern part of the urban area, in a residential neighborhood with a much lower building density (λ_P =0.2) and a H/W=0.1.

In Figure 5, the diurnal evolution of the mean radiant temperature in the six points (three per street direction) is presented for the high urban density point and the low urban density point. During the daytime, the impact of the shadowing is clear, with reduced mean radiant temperature in the high-density point compared to the more exposed low-density. On the other hand, during nighttime, the reduced sky-view factor in the high-density point slows down the cooling compared to the more open low-density location.

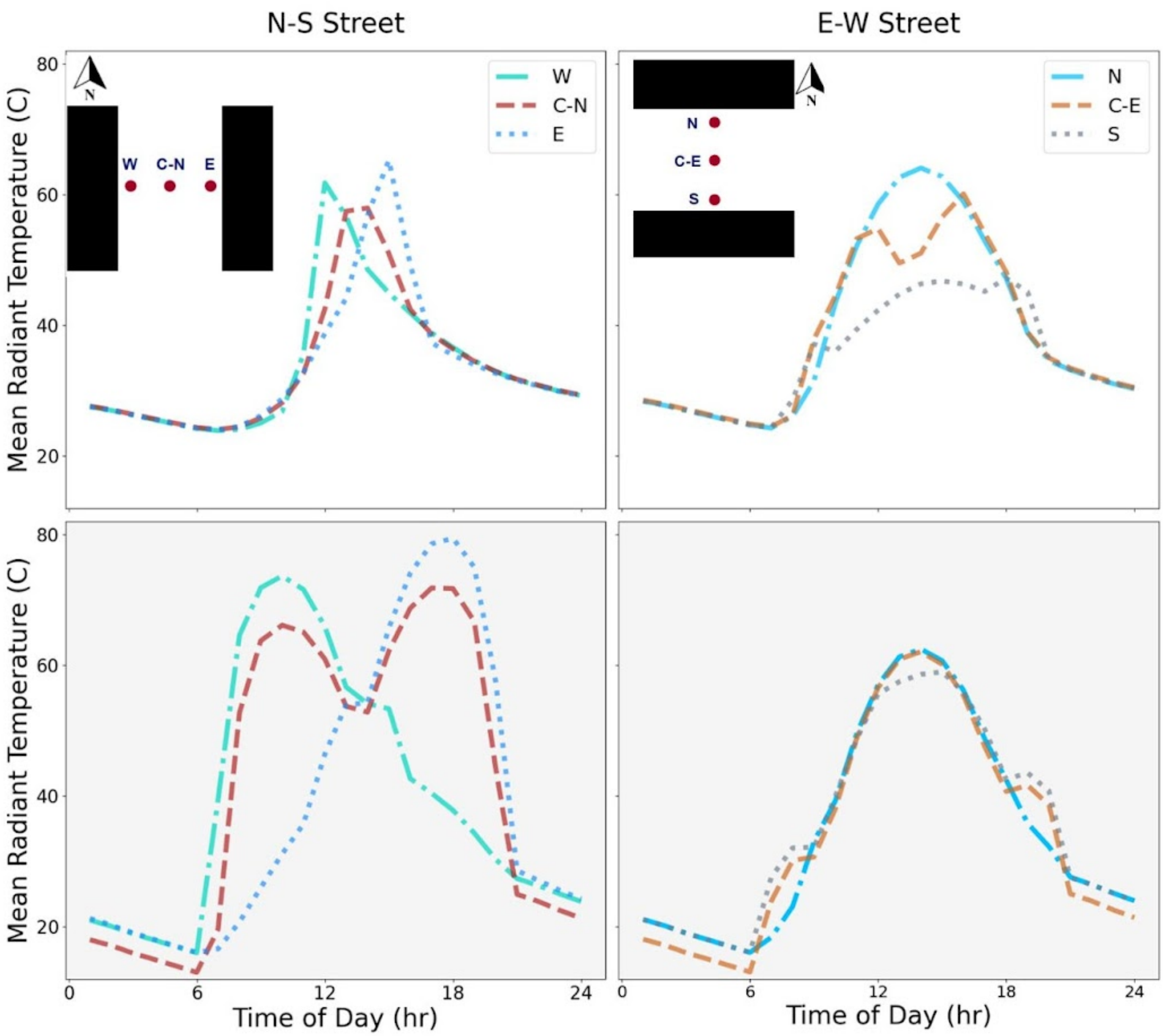

Figure 5. Diurnal evolution of MRT for 6 points in the urban canopy. The top row (white background) corresponds to a grid with the highest building density in the center of Madrid (λ_P =0.69) while the bottom row (with grey background) shows MRT in a low-density neighborhood (λ_P =0.19). The left column is for an N-S street, while the right column shows an E-W street.

This behavior helps to explain the heat stress index (Figure 6). The air temperature indicates hotter values both during the day and the night in the high urban density point compared to the low-density location. The Heat Index, which considers air

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temperature and humidity only, and does not include mean radiant temperature or wind, shows the same tendency. On the other hand, the UTCI behavior communicates a different and more complete result. In the low-density neighborhood, more exposed to the sun, the UTCI shows a stronger sub-grid spatial variability, in particular during the morning and afternoon, with the potential for stronger heat stress than in the high-density neighborhood. During nighttime, the spatial variability is reduced, due to reduced MRT variation as the shadowing effect disappears, and higher UTCI values are found at the high urban density location. This difference in behavior between the two locations can be seen also in Fig. 7, where the fractions of the 10th percentile of UTCI values (i.e. representative of one of the coolest spots in the grid cell) and the 90th percentile (i.e., one of the hottest) in the different heat stress regimes are shown for the two points. Here we can see that in the low-density urban point, the cool location is in a comfortable UTCI range most of the time, while the hot (90th percentile UTCI) subgrid location is under stress most of the time. On the other hand, less variability is present in the high-density neighborhood, with fewer extreme values, and most of the time in the strong or moderate heat stress regime for both the cool and hot locations within the grid square. This kind of detail is not available from the Heat index distribution which does not account for the mean radiant temperature, wind, or their variabilities (Fig. 8).

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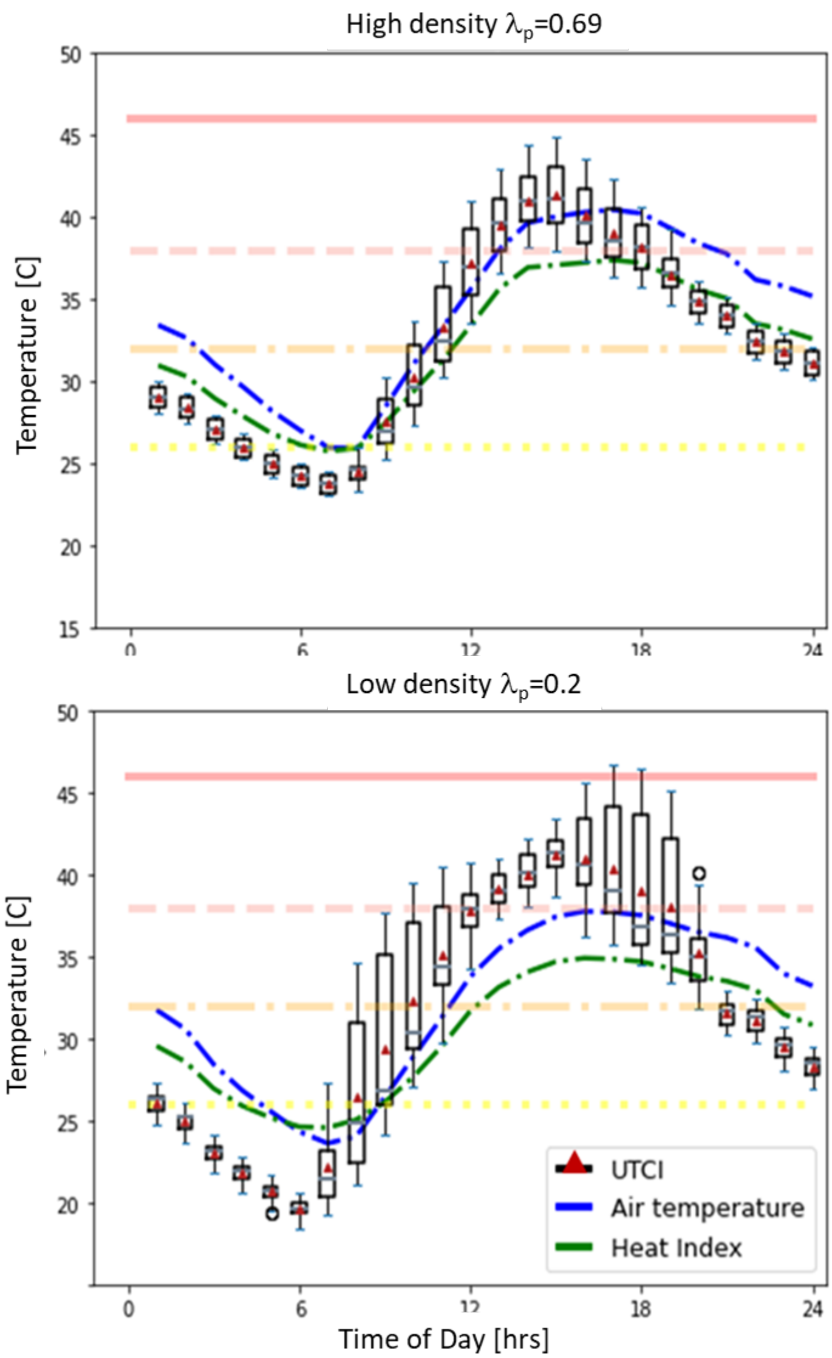

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247 **Figure 6.** Diurnal evolution of UTCI compared with 2-m air temperature and heat index calculated from air temperature and relative
248 humidity at each grid point). The UTCI boxplot at each hour represents the subgrid-scale distribution calculated based on 6 MRT, 3 wind
249 speeds, and 3 air temperature values (54 combinations in total). The horizontal lines represent the thermal comfort zones for UTCI (i.e.

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above +46C: extreme heat stress; +38 to +46: very strong heat stress; +32 to +38: strong heat stress; +26 to +32: moderate heat stress; and +9 to +26: no thermal stress).

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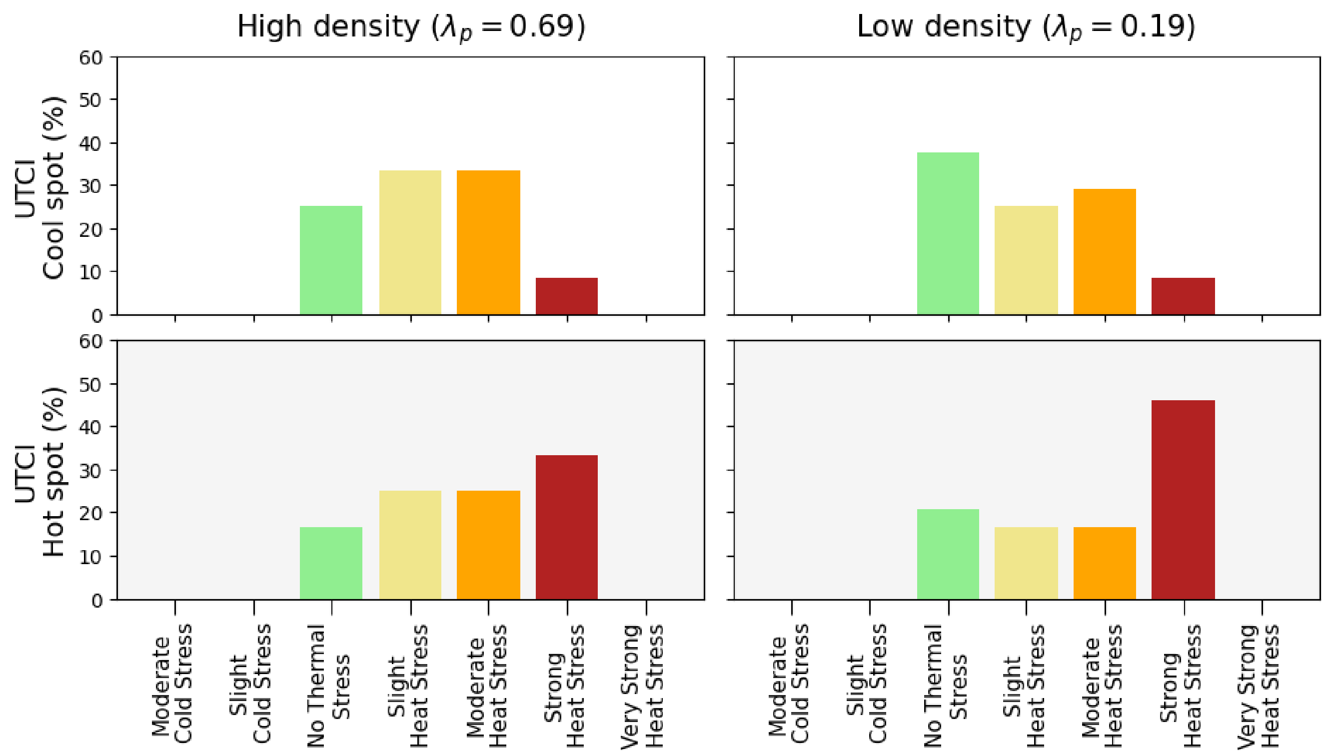

Figure 7. From top to bottom, the frequency of UTCI class over a 24-hour period, for a subgrid location that is cooler (i.e. 10th percentile of UTCI in the urban canopy, top), and for a subgrid location that is hotter (i.e. 90th percentile of UTCI in the urban canopy, bottom), for the high-density (left) and low-density (right) points.

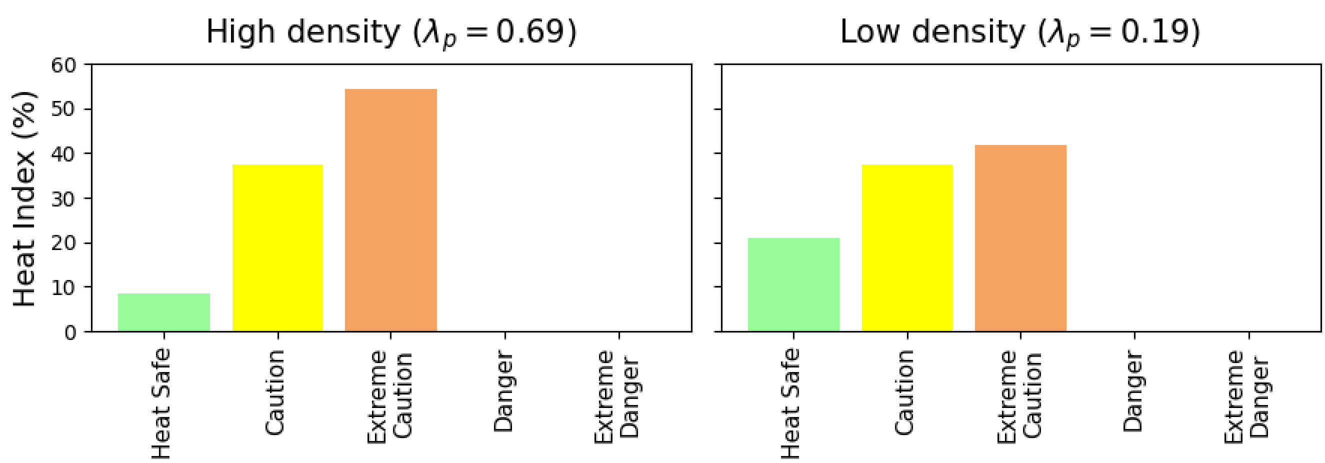

Figure 8. same as Figure 7, but for the Heat Index

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3.2 City-scale maps of outdoor thermal comfort and heat stress indicators.

The previous analysis helps to understand the spatial distribution of the different variables presented in Fig. 9 at 10 and 16 UTC (note that Madrid is at Longitude 3W, so UTC is essentially equal to solar time). The distribution of 2m air temperature at 9 UTC shows a hot region in the dense city center, with cooler areas in the less dense regions around it. This effect is due to the fact that in the dense region, the reduced sky-view factor of the streets (high H/W), as well as the larger thermal storage in the buildings, reduce the nocturnal cooling, and increase the vertical mixing in that part of the city compared to the surroundings. Such a difference is still visible in the morning. The higher temperatures in the S-E part of the urban area, and cool temperatures in the N-W are the result of the topographical differences. The spatial distribution of air temperature is qualitatively similar to the spatial distribution of the 10-percentile of UTCI (e. g. the cool spot in the grid cell), even if the differences between the center and the surrounding urban areas are not as intense as for 2m air temperature. On the other hand, the 90-percentile map (hot spot), shows a completely different pattern, due to the fact that in the city center, at that time of the day, the whole street is still in the shadow, while in the surrounding, less dense urban areas there are points completely exposed to the sun. As a comparison, the map of surface temperature (a variable often used to represent the spatial distribution of heat in cities) as seen from a satellite, i.e. based only on a weighted average of roof, street, and vegetation temperatures (see full equations in Martilli et al. 2021), does not show a clear pattern, and it is uncorrelated with the other maps. This is a clear indication that this variable should not be used for the assessment of the heat hazard or heat stress in urban areas.

At 1600 UTC the air temperature shows again higher values in the city center, lower in the urban surroundings, and a gradient from hotter S-E at lower elevations to cooler N-W at higher elevations (Fig. 10). Such a tendency is present also for the 10th percentile (cool spot), but with less variability. The 90th percentile map (hot spot) indicates that the area with elevated heat stress extends well beyond the city center, including lower-density regions that, even if they have lower air temperatures, are fully exposed to the sun. Finally, as it was the case for 09000 UTC, the surface temperatures have a map uncorrelated with neither the air temperatures nor the UTCI maps.

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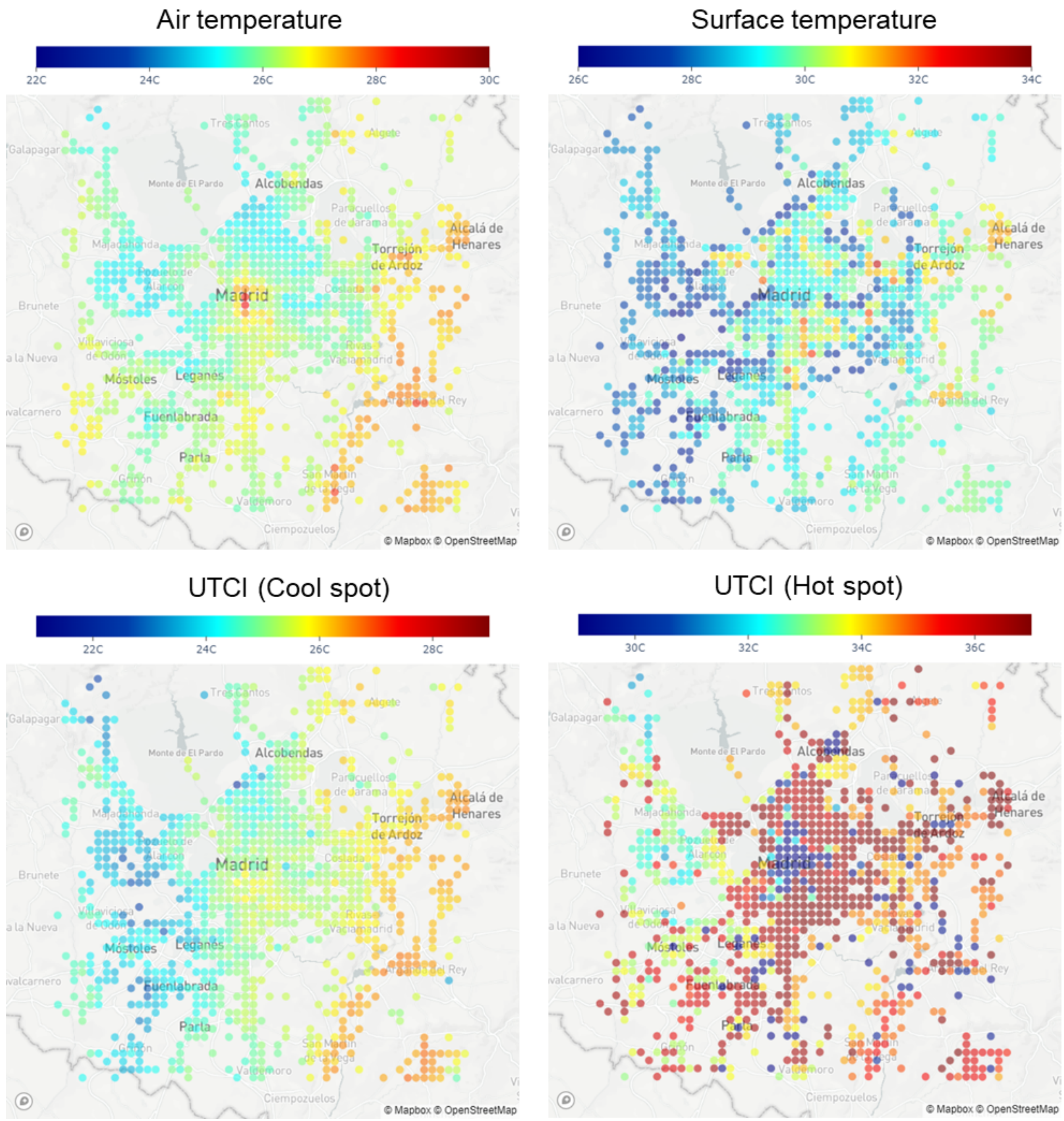

Figure 9. Spatial maps at 0900 UTC for 2-m air temperature (top left), surface temperature (top right), UTCI cool spot e. g. the 10 percentile of UTCI captured in the urban canopy model (bottom left), and UTCI hot spot e. g. 90 percentile of UTCI in the urban canopy (bottom right). Surface temperature is equivalent to that seen by a nadir-view satellite sensor (i.e., an area-weighted average of canopy ground temperature, roof temperature, and vegetation temperature in non-urban fractions is considered). The underlying maps were created with Mapbox OpenStreetMap

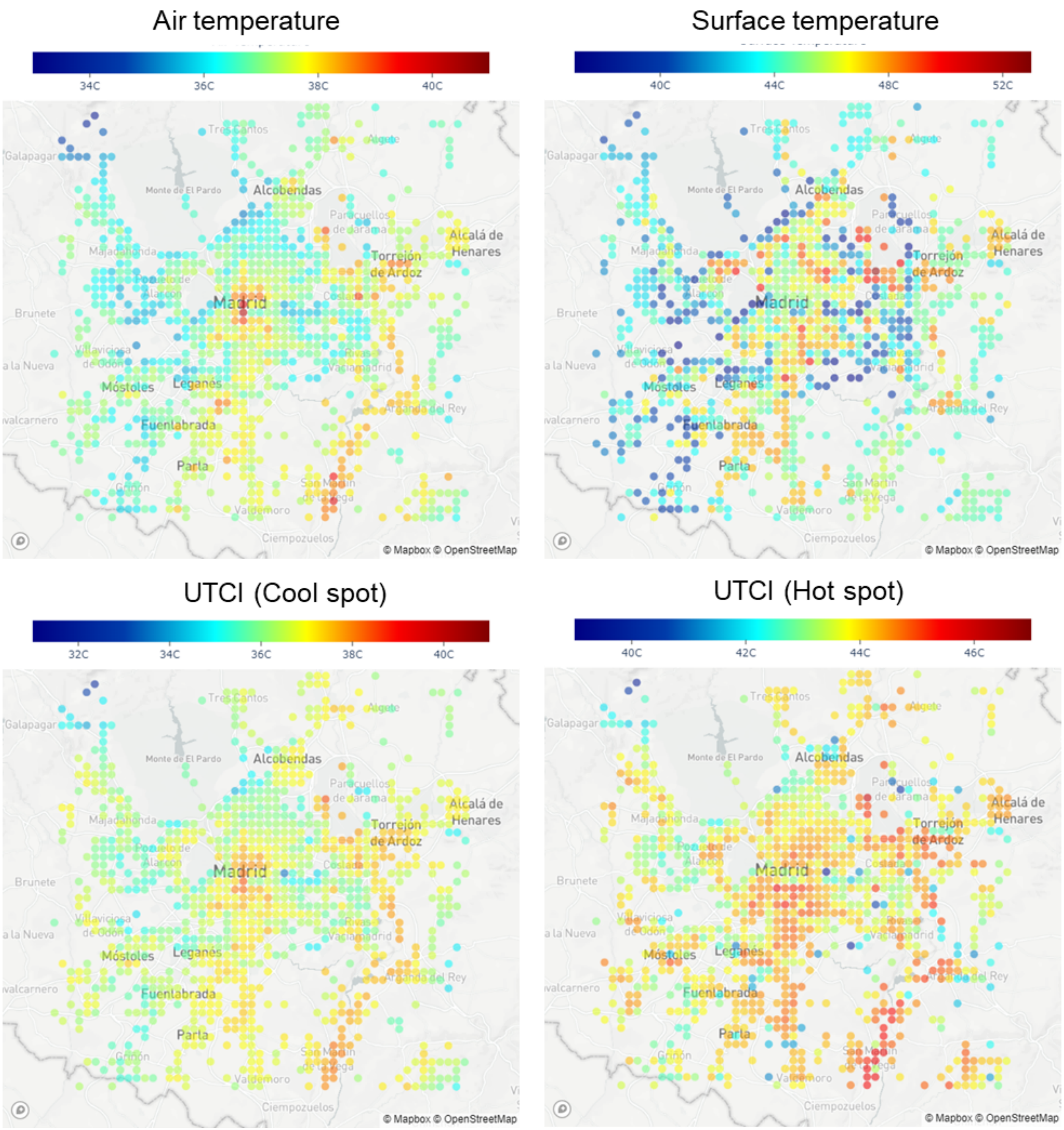

Figure 10. Same as Figure 9, but at 1600 UTC.

4. Conclusions

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A new parameterization to quantify intra-neighborhood heat stress variability in urban areas using a mesoscale model is presented. This approach is based on two primary developments: 1) calculation of mean radiant temperature at several locations within the idealized urban morphology used by the urban canopy model BEP-BEM; and 2) parameterization of mean wind speed and its sub-grid spatial variability as a function of the local urban morphology and the mean wind velocity computed by the WRF mesoscale model, using relations developed from a large suite of CFD simulations over a range of realistic and idealized urban neighborhoods. The components of the new parameterization have been validated against microscale model results. From this approach the sub-grid variability of a heat stress index (i.e. UTCI or SET) can be computed for every grid point, permitting quantification of the heat exposure at both cool and hot locations within each grid square at each time.

The new parameterization has been implemented in the multilayer scheme BEP-BEM in WRF and used to simulate a heatwave day over Madrid (Spain) as proof of concept. The results of this initial application demonstrate the following:

I. The new parameterization gives information that is more suitable for the evaluation of heat stress than the air temperature, being based on an index (UTCI or SET) that also combines air humidity, wind speed, and mean radiant temperature.

II. The new parameterization provides substantively more information than air temperature alone (or any other index that does not account for the mean radiant temperature). It provides information about the sub-grid variability (such that heat stress in both cool and hot locations in each grid square is quantified). To our knowledge, this has never been done before with a mesoscale model.

III. The results for the investigated case, indicate a strong intraurban variability, both in air temperature and UTCI values, that can be linked to the differences in urban morphology and elevation above sea level. The ability to assess the differential impacts of urban morphology on heat stress is key to the provision of guidance for urban planning strategies that mitigate urban overheating.

IV. Nadir-view surface temperature (i.e., as seen from a satellite-mounted remote sensor) is poorly correlated with both air temperature and UTCI maps, indicating that, despite its ubiquitous use at present, it is unlikely to be an adequate metric for heat impact assessment studies.

Finally, we consider that this new development introduces a new methodology for deploying mesoscale models to assess urban overheating mitigation strategies.

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Code Availability

The code of WRF-comfort can be obtained here:

https://doi.org/10.5281/zenodo.7951433

The results of the simulation over Madrid shown in the manuscript are stored here:

https://zenodo.org/record/8199017

Competing interests

The authors declare that they have no conflict of interest

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Appendix A. Comparison of Short wave calculation in BEP-BEM and TUF-pedestrian.

Short wave radiation is an essential component of the MRT. Below we compare the short wave radiation reaching the vertical sides of the segment representing the human body computed by BEP-BEM vs those estimated with the more detailed model TUF-pedestrian.

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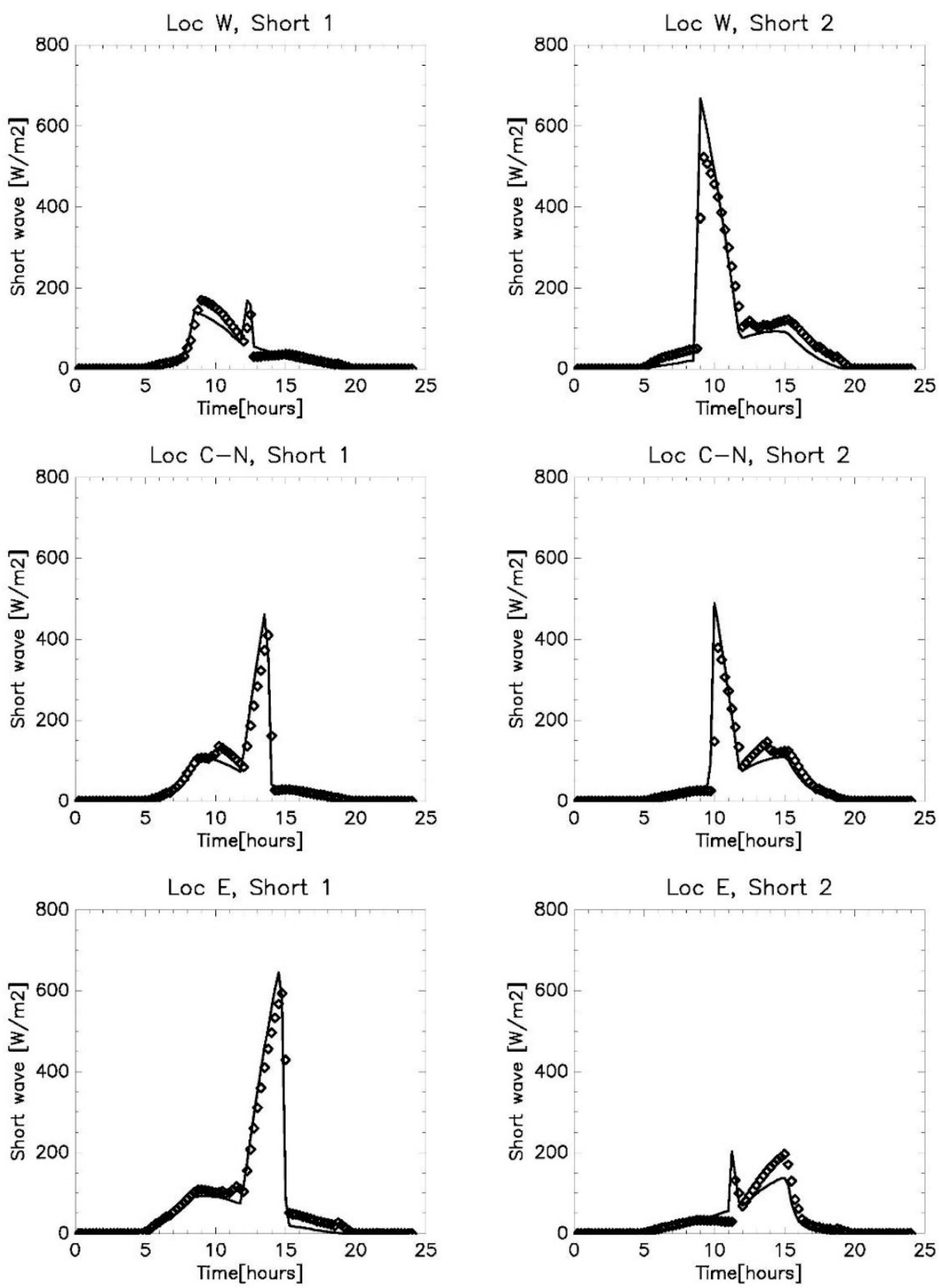

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453 Figure A1. Comparison of short wave radiation at the two sides of the vertical segment representing the pedestrian for the
454 N-S oriented street. Solid line is the WRF, while diamonds are TUF

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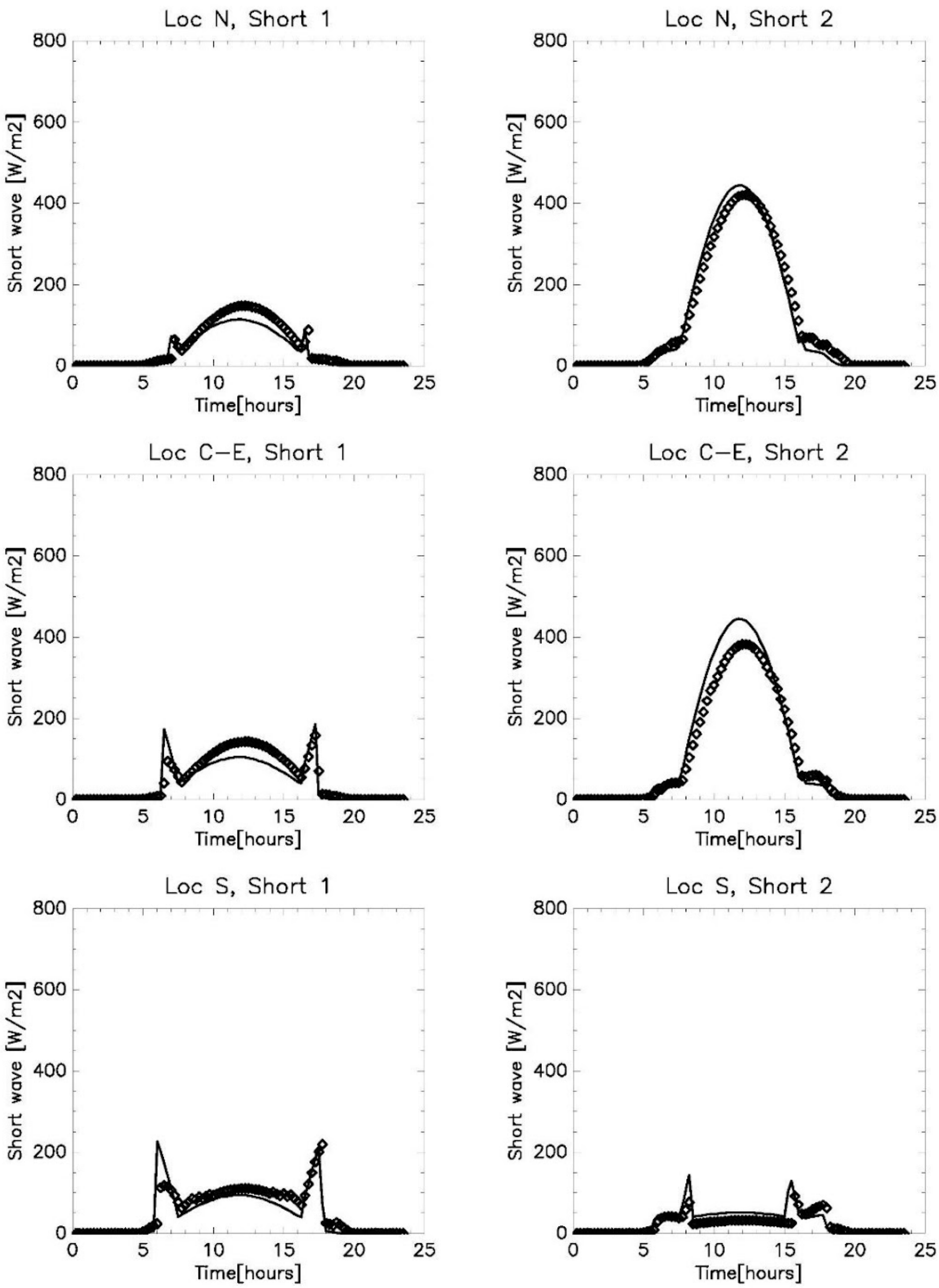

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457 Figure A2. Same as S1, but for a E-W oriented street

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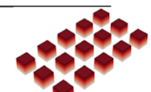
Appendix B. CFD simulations for wind speed variability

Data from over 173 microscales CFD simulations of urban airflow are considered over realistic and idealized urban configurations, spanning a wide range of building plan area (λ_P), frontal area (λ_F), and wall area (λ_w) densities representative of realistic urban neighborhoods in different types of cities. CFD simulations are conducted using 162 large-eddy simulations (LES) and 11 Reynolds-averaged Navier–Stokes (RANS) schemes detailed in Table B.1.

Table B.1 Details of CFD microscale simulation cases considered in this study. Simulations are classified based on the configuration (urban form) used. These classifications include **UA** (**U**niform height with **A**ligned configuration), **US** (**U**niform height with **S**taggered configuration), **VA** (**V**ariable height with **A**ligned configuration), **VS** (**V**ariable height with **S**taggered configuration), **UR** (**U**niform height with **R**ealistic configuration), and **VR-WD** (**V**ariable height with **R**ealistic configuration and multiple **W**ind **D**irections considered).

Model	Classification	H_m[m]	H_{max} [m]	λ_p range	Count	Source	Example
LES	UA	16	16	[0.0625 - 0.64]	7	Nazarian et al. 2020 Lu et al. 2022	
LES	US	16	16	[0.0625 - 0.64]	7	Nazarian et al. 2020 Lu et al. 2022	
LES	VA	16	20, 24	[0.0625 - 0.64]	42	Lu et al. 2022 Lu et al. 2023	
LES	VS	16	20, 24	[0.0625 - 0.64]	42	Lu et al. 2022 Lu et al. 2023	
LES	UR	16	16	[0.057 - 0.536]	64	Lu et al. 2022	
RANS	VR-WD	14.5-34	variable	[0.190 - 0.680]	11	Sanchez et al. (2017) Santiago et al. (2017) Kracht et al. (2017) Borge et al. (2018) Kracht et al. (2019) Santiago et al. (2020) Sanchez et al. (2021)	

In the LES simulations, airflow over idealized and realistic urban arrays to determine the model parameters (Nazarian et al., 2020; Lu et al., 2022, 2023). Realistic urban layouts are prepared by rasterizing building footprints from an open-source

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dataset OpenStreetMap using OSM2LES (Lu et al., 2022). 64 realistic urban neighborhoods were obtained assuming uniform building height (Table B.1) from several major cities such as Sydney and Melbourne (Australia), Barcelona (Spain), Detroit, Los Angeles, and Chicago (United States). Idealized urban arrays are considered in aligned and staggered arrangement that follows (Coceal et al., 2007) with varying urban density (λ_p in [0.0625,0.64]) and height variability (H_{std} =[0m,2.8m,5.6m]). Simulations are conducted in the Parallelized Large-eddy Simulation Model (PALM, version r4554) (Maronga et al., 2020) following the same setup in (Nazarian et al., 2020), which has validated results against Direct Numerical Simulation (Coceal et al., 2007) and wind tunnel experiments (Brown et al., 2001). The computational domain is discretized using the second-order central differences (Piacsek and Williams, 1970) where the horizontal grid spacing is uniform and the vertical spacing follows the staggered Arakawa C-grid. The minimal storage scheme is employed in the time integration to solve the filtered prognostic incompressible Boussinesq equations where the pressure perturbation was calculated in Poisson's equation and was solved by the FFTW scheme (Frigo and Johnson, 1998).

The RANS dataset is derived from steady-state CFD-RANS simulations performed with the Realizable k- ε turbulence model (STAR-CCM+, Siemens) over realistic urban areas. The size of the computational domains is determined following the best practice guideline of COST Action 732 (Franke et al., 2010). The horizontal area covers around 1-1.5 km2 and the domain top is at around 8H, being H the mean height of buildings. The resolution of the irregular polyhedral mesh used in all CFD-RANS simulations goes from 0.5 m close to buildings to 6 m out of the built-up area, which results in between 3 and 8 million grid points depending on the complexity of the geometry. Inlet vertical profiles for wind speed, turbulent kinetic energy (k), and its dissipation (ε), are established in neutral atmospheric conditions. The evaluation of the CFD-RANS simulations was addressed in previous studies summarized in Table B2 and more information is provided in previous publications.