

GLIDE-SOL: A GPU-accelerated Global Lightweight Infrastructure for Diagnostic Environmental Modeling with SOLWEIG

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Abstract. GLIDE-SOL is a fully scripted and globally re-deployable Python workflow that operationalizes SOLWEIG for rapid and repeatable thermal-comfort mapping across diverse urban environments. GLIDE-SOL is built on the SOLWEIG radiative balance libraries, but rewrites the surrounding system—including automated input generation, the execution engine, and post-processing—so that the model can be driven by globally available datasets and executed efficiently on GPUs. All inputs (terrain, building morphology, canopy height, land cover, and meteorology) are automatically derived from global products, eliminating local preprocessing while enabling consistent applications from neighborhood-scale analyses to city-wide and multi-city experiments. In addition, GLIDE-SOL introduces lightweight physical diagnostics to improve realism when driven by coarse meteorological forcing, targeting key urban controls on wind and near-surface temperature.

The workflow incorporates two physical augmentations: (i) roughness- and obstacle-based directional wind attenuation to approximate near-surface ventilation; and (ii) diagnostic temperature adjustments that combine a simple urban heat island (UHI) cycle with an elevation-based correction using high-resolution DEM information, to better capture nocturnal warming and local lapse-rate effects.

To scale to large metropolitan areas, GLIDE-SOL uses explicit domain tiling with cross-tile synchronization to preserve radiative consistency across tile boundaries, enabling meter-scale simulations over tens to hundreds of square kilometers without sacrificing reproducibility. Daily outputs (24 radiative and meteorological fields) are stored as compressed GeoTIFFs to reduce disk usage and accelerate downstream processing.

GLIDE-SOL is implemented through three reproducible components: an automated global-input generator; a SOLWEIG execution engine with coordinated tiling; and a post-processing module for systematic sampling, time-series extraction, and visualization. An operational demonstration in Dortmund, using hourly measurements from 25 urban and peri-urban stations and simulations run at 2 m grid spacing between August 2024 and December 2025, shows that incorporating wind attenuation

and the diagnostic temperature corrections substantially improves UTCI performance (RMSE reduced from 9.98.09 °C to 2.72.84 °C), alongside improvements in T_{mrt} , air temperature, and wind speed simulations.

By integrating harmonized global inputs with physics-based diagnostics, GPU acceleration, and scalable tiling, GLIDE-SOL supports applications such as operational UTCI nowcasting, retrospective and climatological analyses of heat stress, sensitivity tests of urban morphology and greening strategies, and coordinated multi-city experiments requiring consistent modeling protocols.

1 Introduction

Fast and transferable urban thermal-comfort modeling is increasingly required for climate-adaptation planning, operational heat warnings, and systematic inter- and intra-city assessments. Exposure to urban heat stress is shaped by large-scale atmospheric conditions and fine-scale variations in radiation, wind, urban form, and surface cover, with pronounced differences between neighborhoods, street canyons, and open spaces (Emmanuel and Fernando, 2007; Mayer et al., 2008). Urban heat islands, particularly at night, and uneven daytime exposure to high radiant loads and locally reduced wind speeds contribute to elevated heat-stress risk (Oke et al., 2017). Radiant load, often expressed through mean radiant temperature (T_{mrt}), is a crucial meteorological driver of human energy balance and thermal comfort during warm, clear conditions (Mayer and Höppe, 1987; Thorsson et al., 2007). T_{mrt} is a key input to bio-climatic indices such as the Physiological Equivalent Temperature (PET) and Universal Thermal Climate Index (UTCI) (Höppe, 1999; Fiala et al., 2012; Jendritzky et al., 2012), which combine radiation, air temperature, humidity, and wind speed into a single thermal-stress metric (Cheng et al., 2012).

T_{mrt} arises from the net shortwave and long-wave radiation fluxes from all surrounding surfaces and the sky. While intra-urban air-temperature differences are often modest during the day, T_{mrt} can exhibit strong spatial variability over distances of only a few meters (Lindberg and Grimmond, 2011a, b; Thorsson et al., 2011; Middel and Krayenhoff, 2019). These microscale variations are primarily driven by shadow patterns created by buildings, trees, and topography, as well as by differences in surface radiative and thermal properties such as albedo, emissivity, and heat capacity (Thorsson et al., 2007; Konarska et al., 2014; Lindberg et al., 2016). The SOLWEIG (*SOLar and LongWave Environmental Irradiance Geometry*) (Lindberg et al., 2008) model is widely used to estimate T_{mrt} and related thermal-comfort indices in complex urban environments. It resolves shortwave and longwave radiation fluxes in three dimensions and has been applied to analyze the influence of urban geometry, ground surfaces, and vegetation on outdoor thermal comfort in a variety of climates, and validated against ground observations (Lindberg and Grimmond, 2011a, b; Briegel et al., 2024; Buo et al., 2023). SOLWEIG is also integrated in the Urban Multi-scale Environmental Predictor (UMEP) (Lindberg et al., 2018), which provides a QGIS-based environment for linking urban-climate models with geospatial data to support climate services, heat-risk assessments, and planning applications. Despite its strong theoretical foundation and broad adoption in case studies, SOLWEIG has not yet matured into a globally operational tool.

Several persistent barriers limit the wider deployment of SOLWEIG for city-wide or multi-city applications. First, realistic setups typically require detailed, locally assembled input data: high-resolution digital elevation/surface models, building land

cover, footprints and heights, vegetation structure, and representative meteorological forcing (Jänicke et al., 2016; Zonato et al., 2020). These inputs are often derived from local LiDAR campaigns, city-specific GIS databases, or bespoke classifications, which are not uniformly available across regions. Second, microscale radiative models can be computationally demanding when applied at meter-scale resolution over large urban domains or long simulation periods (Toparlar et al., 2017; Briegel et al., 2024). Third, near-surface wind is frequently prescribed from single meteorological stations or coarse reanalyses that do not explicitly account for building-induced sheltering and channeling, even though wind strongly modulates thermal comfort (Cionco, 1972; Chu and Wang, 2025). CFD models such as ENVI-met and PALM-4U can resolve pedestrian-level wind and temperature fields (Simon, 2016; Maronga et al., 2020), but their computational cost generally restricts their use to micro-scale domains or limited simulation periods.

In parallel, global geospatial and meteorological datasets have advanced to the point where they can serve as a common input backbone for urban climate applications. ESA WorldCover provides 10 m global land-cover classes suitable for distinguishing major urban and vegetated surfaces (Zanaga et al., 2022). On the terrain side, MERIT DEM (Yamazaki et al., 2017) offers harmonized global elevation information at 3-arc-second (90 m) resolution, forming a consistent basis for topographic inputs.

Complementing these terrain-only products, a new generation of [global-open](#) building datasets has emerged, providing both footprints and 3D attributes essential for urban climate modeling. ~~OpenStreetMap (OpenStreetMap contributors, 2017) supplies global building polygons, while dedicated building datasets now include UT-GLOBUS (Kamath et al., 2024), offering 3-m building-height estimates worldwide; GlobalBuildingAtlas (Zhu et al., 2025), providing global~~ [Microsoft global building footprints \(Microsoft, 2026\), Overture Maps building footprints \(Overture Maps Foundation, 2026\), and GlobalBuildingAtlas LoD1 building geometries at 3-m resolution; GeoClimate's height-completed OSM layers \(Bernard et al., 2022\), which add locally calibrated height estimates; and the recently released OpenBuildingMap dataset \(Oostwegel et al., 2025\), which integrates multiple global sources to produce harmonized building footprints enriched with semantic attributes such as height, floors, and function. Together, these building datasets deliver near-global coverage of 3D urban morphology, enabling more realistic city- and street-scale simulations worldwide.](#) [buildings \(Zhu et al., 2025\) provide a practical multi-source basis for assembling building footprints across regions with very different input-data availability. Building-height attribution can then be supported by products such as GlobalBuildingAtlas and OpenBuildingMap \(Oostwegel et al., 2025\).](#)

At the same time, global canopy-height products have also matured rapidly: very-high-resolution (1 m) tree-height maps derived from self-supervised deep learning trained on airborne LiDAR (Tolan et al., 2024), the global canopy height model by Lang et al. (Lang et al., 2023) at 10 m resolution, and the GEDI-based Canopy Height Mapper (Potapov et al., 2021), which delivers canopy heights at 30 m resolution through a Google Earth Engine workflow, collectively provide consistent estimates of vegetation height and distribution. Together, these resources supply a coherent global basis for representing not only terrain and buildings but also the three-dimensional distribution of urban and peri-urban vegetation. [In dense urban settings, however, narrow streets, building shadows, and mixed pixels can still affect canopy detection. The resulting tree layer is therefore used here as a globally consistent approximation of urban vegetation structure, while local mapping errors are treated as part of the input-data uncertainty.](#)

On the meteorological side, the ERA5 reanalysis provides globally consistent, hourly atmospheric fields (Hersbach et al., 2020). However, its coarse resolution inherently limits the representation of mesoscale and, especially, urban-scale processes: even when dynamically down-scaled, ERA5 tends to smooth local thermal gradients and fails to capture city-specific features and extreme conditions (Adinolfi et al., 2023). Platforms such as Google Earth Engine enable planetary-scale access and processing of these datasets in a reproducible, scriptable manner (Gorelick et al., 2017).

Recent studies demonstrate that city-wide, building-resolving thermal-comfort mapping with SOLWEIG and UMEP is now feasible using scripted workflows. Jänicke et al. (2016) performed a city-wide analysis of T_{mrt} at building resolution, while more recent work has produced high-resolution thermal exposure and shade maps to support cool-corridor planning (Buo et al., 2023). A key recent example is the study by Lindberg et al. (2025), who applied UMEP–SOLWEIG at 2 m resolution across Stockholm, Gothenburg, and Malmö to quantify how building density, tree fraction, and ground cover shape PET, UTCI, T_{mrt} , and pedestrian wind speed during heatwaves.

At the same time, GPU-based approaches to urban heat mapping have shown that large-domain, high-resolution simulations can be substantially accelerated. Li and Wang (2021) report over 99% speed-up in computing city-scale heat-exposure metrics from high-resolution surface data. Yang et al. (2023) achieve near-real-time urban LES using a multi-GPU framework that preserves building-resolving detail. Similarly, the multi-scale City-LES v2.0 model (Kusaka et al., 2024) exploits GPU clusters to efficiently couple mesoscale and microscale LES, enabling long-duration, building-explicit simulations with full radiative calculations. Likewise, Li et al. (2024) employs GPU-accelerated computation to assess heat sensitivity and vulnerability across major U.S. cities, demonstrating that large-scale exposure analyses can now be carried out with operationally feasible runtimes.

In addition, recent open-source work has demonstrated how the core SOLWEIG radiative-geometry and time-stepping calculations can be refactored for GPU execution. SOLWEIG-GPU  provides a Python implementation that runs SOLWEIG (v2022a) on GPUs via a simple API, CLI, or GUI, and targets meter-scale, city-scale domains by combining domain tiling with GPU-parallelized computation of SVF, T_{mrt} , shadows, and UTCI (while wall height and wall aspect remain CPU-side and are parallelized across cores) ([Kamath et al., 2026](#)).

Reported benchmarks show substantial acceleration for the SVF+UTCI core: for tile sizes of 1000×1000 , 1500×1500 , and 2000×2000 cells, runtimes decrease from 1187, 3322, and 6487 s on a CPU workstation to 47, 105, and 158 s on an NVIDIA A6000 GPU, corresponding to approximately $25\times$, $32\times$, and $41\times$ speed-ups. This work served as a practical reference point for the GPU-oriented design choices adopted in GLIDE-SOL.

The goal of GLIDE-SOL (Global Lightweight Infrastructure for Diagnostic Environmental modeling with SOLWEIG) is to transform SOLWEIG from a case-specific research tool into a reproducible, globally deployable workflow. GLIDE-SOL rests on three pillars. First, all required input data are obtained from globally or regionally available datasets—including ESA WorldCover (Zanaga et al., 2022), MERIT DEM (Yamazaki et al., 2017), GlobalBuildingAtlas (Zhu et al., 2025), and ERA5 accessed and processed via Google Earth Engine (Gorelick et al., 2017; Hersbach et al., 2020)—and automatically transformed into SOLWEIG-ready rasters. Second, GLIDE-SOL incorporates diagnostic physical modules designed to compensate for limitations of coarse meteorological forcing in urban settings: a Röckle-style directional wind-attenuation scheme (Röckle, 1990; Bernard et al., 2023) and a simple urban heat island adjustment informed by urban-climate theory (Theeuwes et al.,

2016). Third, GLIDE-SOL targets scalability and computational efficiency through GPU-accelerated radiative geometry and explicit domain tiling. Entire cities, including large metropolitan areas spanning tens to hundreds of square kilometers, can thus
125 be simulated at meter-scale resolution, with daily outputs stored as compressed GeoTIFFs for efficient downstream analysis.

In this paper, we document the GLIDE-SOL workflow and demonstrate its capabilities in Dortmund, Germany, using a dense observational network of 25 urban and peri-urban stations between August 2024 and December 2025. Simulations are conducted at 2 m grid spacing over the full metropolitan area. We first describe the automated pre-processing pipeline and its use of global datasets, then outline the SOLWEIG configuration, diagnostic wind and Urban Heat Island (UHI) modules,
130 and GPU tiling strategy, and finally present an evaluation of hourly UTCI, T_{mrt} , air temperature, and wind speed against observations. Beyond reporting skill metrics, we discuss operational aspects such as wall-clock time and memory usage, and consider how a global-input, SOLWEIG-based workflow can support operational heat-risk assessment, climatological analysis, urban-planning evaluation, and coordinated multi-city modeling experiments.

2 Materials and methods

135 This section presents the end-to-end methodology of the GLIDE-SOL framework. We first describe the SOLWEIG Preprocessor, which automatically builds a co-registered spatial input stack (rasters and vectors) and harmonizes ERA5 meteorological forcing into SOLWEIG-ready formats. We then outline the GPU-accelerated execution strategy, including tiling, memory management, and CPU/GPU responsibilities for scalable hourly simulations. Finally, we detail the additional physical parameterizations introduced in this work (diagnostic UHI cycle, elevation bias correction, and wind reduction coefficients) that improve realism
140 while preserving a fully reproducible, script-driven workflow based on globally available data sources and standardized processing steps. Figure 1 provides an overview of the complete pipeline.

2.1 Overview of the SOLWEIG core

SOLWEIG (*Solar and LongWave Environmental Irradiance Geometry*) is a three-dimensional radiative model developed to estimate mean radiant temperature (T_{mrt}) and related thermal-comfort quantities from urban geometry, vegetation, sun position,
145 and near-surface meteorological forcing ([Lindberg et al., 2008](#); [Lindberg and Grimmond, 2011a, b](#); [Lindberg et al., 2018](#)) ([Lindberg et al., 2024](#)). At each time step, the model combines direct, diffuse, and reflected shortwave radiation with longwave exchange from sky, ground, walls, and vegetation to resolve the radiative environment experienced by a pedestrian, from which T_{mrt} and derived indices such as UTCI can be computed. This representation has been widely used in urban-climate and outdoor-comfort studies, including intercomparisons with other microclimate models and evaluations against observations (Aydin et al., 2019; Briegel
150 et al., 2024).

In GLIDE-SOL, this logic is preserved but organized into an explicit, GPU-oriented execution sequence. The solver loads the static morphology layers (`Building_DSM`, `DEM`, `Trees`, `Landuse`, `Walls`, and `Aspect`), computes total and directional sky-view factors (SVF), evaluates building and vegetation shadow masks, and then advances the hourly SOLWEIG radiation balance on each tile before computing T_{mrt} , air temperature adjustments, wind speed, and UTCI. This implementation mirrors

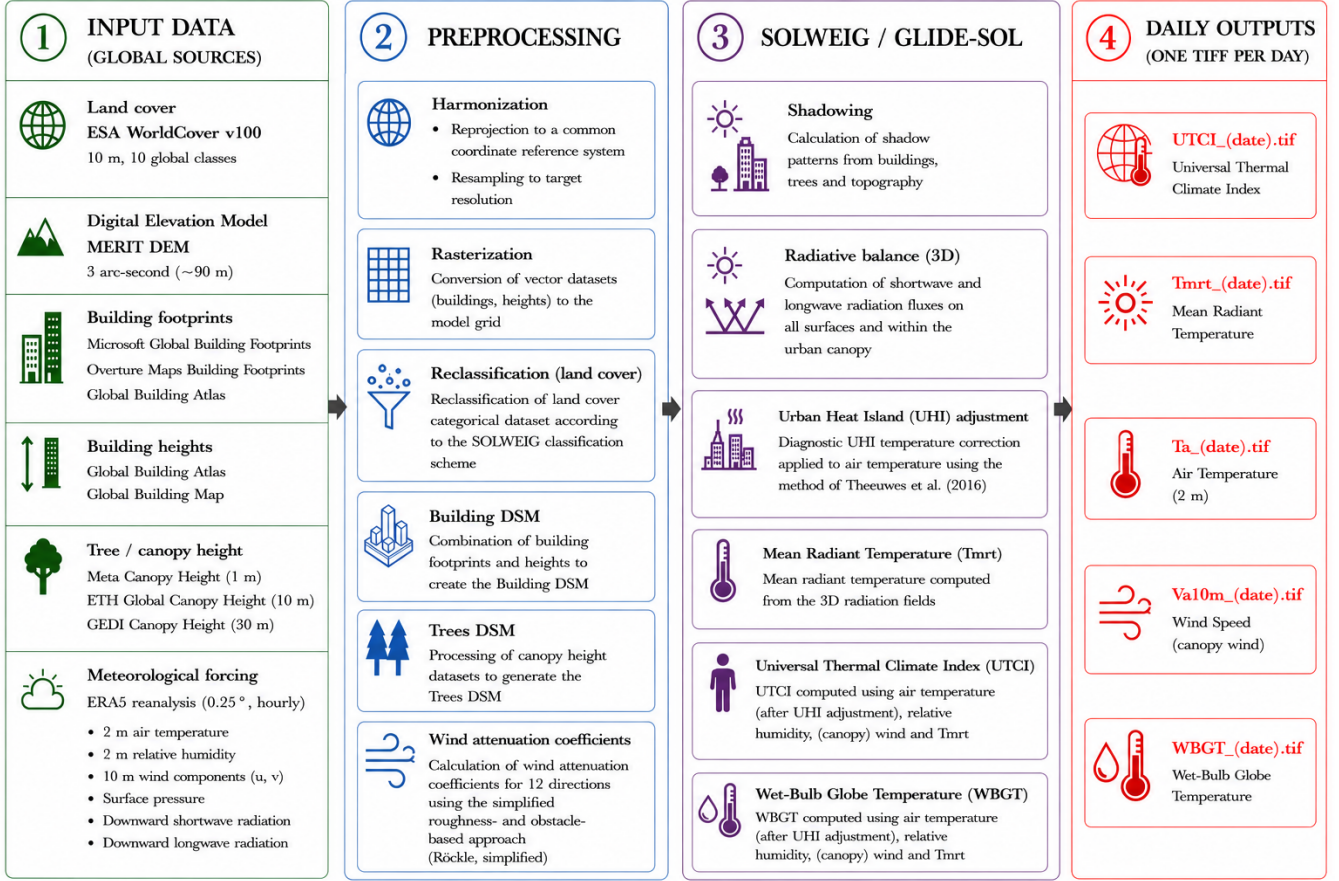


Figure 1. Workflow of the GLIDE-SOL framework.

the standard SOLWEIG radiative structure while exposing the geometry and radiation terms needed for tiled GPU execution in GLIDE-SOL.

For the Dortmund experiments we used the SOLWEIG v2022a radiative core with the anisotropic sky schemes for both diffuse shortwave and longwave radiation. Diffuse shortwave radiation is represented with the Perez et al. (Perez et al., 1993) sky-luminance distribution as implemented in SOLWEIG: instead of assuming an equal diffuse radiance over the visible sky, the diffuse component is distributed over sky-vault patches according to solar position, clearness, and brightness. This affects the directional shortwave load received by a pedestrian, particularly in partly obstructed urban canyons. Longwave irradiance is treated with the anisotropic parameterization introduced for SOLWEIG v2022a, in which sky longwave emission is also resolved over sky patches rather than prescribed as a spatially uniform hemispheric term (Wallenberg et al., 2020, 2023). The human receiver is represented as a cylinder, consistent with the SOLWEIG configuration used for pedestrian T_{ped} .

The input builder assembles a reproducible stack of rasters and vectors from a latitude/longitude seed, relying on globally accessible sources. The emphasis is to avoid bespoke digitization and to keep decisions transparent and scriptable:

- **Grid and Coordinate Reference System (CRS):** starting from a target latitude–longitude pair, the script automatically selects the appropriate UTM zone, builds a geographic bounding box, and defines a regular metric grid (square pixels).
170 All subsequent rasters (land cover, DEM, trees, buildings, wind coefficients) are reprojected and resampled onto this common grid, so that masking, sampling, and spatial statistics are perfectly co-registered.
- **Land cover, WorldCover reclassification, and elevation:** the script downloads ESA WorldCover 2020 version 2 (Zanaga et al., 2022) for the study area and reclassifies it into a small set of land-use classes tailored to SOLWEIG:
 - 1: urban (WorldCover code 50),
 - 175 – 2: vegetation (default class for all other codes),
 - 3: water (WorldCover codes 80, 70, 90),
 - 4: bare & sand (WorldCover code 60).

The reclassified raster is saved as `Landuse.tif`. In parallel, the script downloads and clips a digital elevation model (DEM), using a high-resolution global product such as MERIT DEM ((Yamazaki et al., 2017), 90 m), and resamples it to
180 the same grid as `DEM.tif`. The DEM is later used to apply an elevation-based correction to ERA5 2 m air temperature (Section 2.4.2).

- **Urban form:** the ~~script ingests LoD1 building heights from the Global Building Atlas ((Zhu et al., 2025), 3 m), together with building footprints and impervious surfaces from OpenStreetMap. These layers are~~ current preprocessor uses a multi-source building workflow. Building footprints can be assembled from a configurable priority order of Microsoft global building footprints (Microsoft, 2026), Overture Maps (Overture Maps Foundation, 2026), and GlobalBuildingAtlas (Zhu et al., 2025). The workflow first cleans each source, builds a non-duplicated footprint baseline by priority, and then assigns roof heights independently from the available height products. Height attribution is sampled in priority order from GlobalBuildingAtlas (Zhu et al., 2025) and OpenBuildingMap (Oostwegel et al., 2025); remaining gaps are filled with the domain median roof height, and a small lower bound of 2 m is enforced to avoid unrealistically low buildings. The
185 resulting footprint and height vectors are rasterized on the common grid and stacked with land-use information, yielding `Buildings.tif` (building footprints) and `Building_DSM.tif`, computed as `DEM + LoD1-building-heights`roof height.
190

- **Trees:** a high-resolution tree-canopy DSM is downloaded via Google Earth Engine from global canopy-height products, trying three sources in order of priority: (i) Meta Forest Monitoring / CanopyHeight ((Tolan et al., 2024), 1 m), (ii) ETH
195 Global Canopy Height 2020 ((Lang et al., 2023), 10 m), and (iii) a GEDI-based product ((Potapov et al., 2021), 30 m).

The selected canopy DSM is mosaicked and rasterized on the common grid to produce `Trees.tif`, representing tree and woody vegetation cover and height across the domain.

- **Wind coefficients:** using `Buildings.tif`, `Trees.tif`, the script computes 12 directional wind-sheltering rasters `WindCoeff_dirXXX.tif` (one for each 30° sector) based on a Röckle-style wake model. The 30° discretization was selected as a pragmatic compromise: it is fine enough to represent the main directional anisotropy of the street and building layout while keeping pre-processing cost and storage moderate. For each wind direction, the sheltering effect of buildings and trees is propagated downstream, then smoothed (e.g. via Gaussian filtering) and clipped to the SOLWEIG domain to avoid artifacts (Section 2.4.3).
- **Meteorology:** meteorological forcing is harmonized from ERA5 reanalysis (Hersbach et al., 2020), retrieved via Google Earth Engine (Gorelick et al., 2017). ~~The key variables—In the current GLIDE-SOL workflow, ERA5 is sampled at the centre of the model domain and converted into a single city-scale background time series. The forcing includes near-surface air temperature at 2 m (T2M), relative humidity at 2 m (RH2M), downward shortwave and longwave radiation at the surface (SWDOWN and LWDOWN), surface pressure (PSFC), the zonal and meridional wind components at and humidity, surface pressure, 10 m (U10M and V10M) wind components , aerodynamic roughness length (Z0), and surface altitude—are renamed and standardized onto a common time axis, surface altitude, and downward shortwave radiation at the surface ; from these, a diagnostic UHI cycle is derived (Section 2.4.1). ERA5 accumulated downward shortwave radiation is converted to W m^{-2} and used as global horizontal shortwave irradiance. Separate direct and diffuse shortwave components were not taken from ERA5. Instead, the global shortwave irradiance was partitioned within SOLWEIG into direct and diffuse components using clearness-index-based atmospheric transmissivity and the Reindl et al. relations (Reindl et al., 1990) . ERA5 downward longwave radiation is retained in the processed forcing dataset for reproducibility and optional experiments, but it was not prescribed in the Dortmund simulations presented here; longwave exchange was computed by SOLWEIG and distributed with the anisotropic longwave scheme.~~ The final output is a NetCDF file ready to be used as forcing for SOLWEIG, such that the downstream pipeline remains identical regardless of the original meteorological source.

220 2.3 GPU acceleration and parallelization

The GPU strategy in GLIDE-SOL ~~is inspired~~ was informed by the open-source SOLWEIG-GPU implementation ~~by Sudharsan et al. ()~~. ~~While GLIDE-SOL re-architects the surrounding workflow (global input generation, coordinated tiling, and post-processing), this prior work described by Kamath et al. (2026), which~~ provided a valuable reference point for GPU-oriented refactoring of ~~the SOLWEIG~~ SOLWEIG's radiative geometry and time-stepping. GLIDE-SOL builds upon this practical foundation while ~~redesigning the overall workflow, specifically in areas such as global input generation, coordinated tiling, and post-processing.~~

GPU/CPU split and tiling

The most intensive geometric and radiative computations run entirely on the GPU: shadow casting, sky-view factor (SVF) estimation, the hourly SOLWEIG radiation balance, and the UTCI calculation all take advantage of fast, auto-casted GPU math. The CPU is responsible for coordinating the workflow. Before each run, GDAL splits the full spatial domain into tiles—typically around one megapixel each—so that every piece comfortably fits within the available VRAM. Crucially, to ~~prevent-reduce~~ edge effects during the simulation (particularly in neighborhood-dependent calculations such as the sky-view factor), a 10-cell padding is added to the perimeter of each tile. ~~This ensures that the calculations for the cells near the tile boundaries use accurate surrounding data~~ At the 2 m grid spacing used here this corresponds to a 20 m halo, which is sufficient to compute the SVF correctly at tile edges and avoid boundary effects in the simulations. Each GPU processes its assigned tiles day by day. Once the geometric and radiative calculations are complete, the added padding is removed during the final GeoTIFF clipping phase to ensure the output raster precisely matches the original spatial domain, eliminating any boundary artifacts. One CPU process orchestrates the flow per device.

Minimizing host-device transfers

Data movement between CPU and GPU is deliberately kept small. For each tile, only the tile itself and its halo are transferred from host to device. After the computation of an hour, the outputs—UTCI, mean radiant temperature, air temperature, wind speed, and optionally shadows—are sent back to the CPU as float32 arrays. At the end of every simulated hour, both GPU and CPU memory are cleaned (CUDA cache, Python garbage collection, malloc_trim) so that the memory footprint stays flat even over long runs.

CPU I/O and deferred re-compression

All writing and compression duties remain on the CPU. Intermediate GeoTIFFs are written with light ZSTD compression and marked as “ready” once all tiles for a given day and variable have arrived. A dedicated repacking thread then uses GDAL CreateCopy to convert each ready file to the LERC+ZSTD (~~codec. The LERC step is configured with~~ variable-specific maximum absolute errors (~~MAX_Z_ERROR budgets-of-)~~ : 0.15 °C for UTCI, 0.10 °C for T_{mrt} , 0.005 m s⁻¹ for V_{a10m} , and a 2 W m⁻² default for radiative terms), ~~and writes~~ . After successful repacking, a hidden “repacked” marker ~~when finished is written~~. GPU workers wait at day boundaries until these markers appear, ensuring I/O never lags behind the compute tasks.

Memory stability

Overall, memory usage remains tightly controlled: the GPU never holds more than one (or a few) tiles at a time plus the 3D shadow and SVF buffers, while CPU RAM is stabilized through one-time raster loads, periodic cleanup, and deferred heavy compression. The result is a pipeline in which GPU computation and CPU I/O overlap smoothly, maximizing throughput without ever exceeding VRAM or system memory limits.

2.4 Physical parameterizations

We summarize the three added parameterizations that improve on the baseline SOLWEIG formulation.

2.4.1 Diagnostic UHI cycle

260 To represent nocturnal warming that is not resolved in ERA5 near-surface meteorology, we impose a diagnostic UHI cycle that perturbs the background air temperature before the SOLWEIG run. The daily maximum UHI amplitude is estimated using the analytical formulation of Theeuwes et al. (2016), evaluated directly from ERA5 variables. For each day d , the maximum UHI intensity is

$$\text{UHI}_{\max}(d) = \left[\frac{\overline{\text{SWDOWN}}_d}{\rho c_p} \cdot \text{DTR}_d^3 \frac{\left(\frac{\overline{\text{SWDOWN}}_d}{\rho c_p} \right) \cdot \text{DTR}_d^3}{\overline{W}_{10,d}^*} \right]^{1/4}, \quad (1)$$

265 where $\overline{\text{SWDOWN}}_d$ is the daily-mean incoming shortwave radiation, DTR_d the daily temperature range, ρ the air density, and c_p the heat capacity of air, and $\overline{W}_{10,d}^*$ the daily mean 10 m wind speed used for the UHI normalization. In the preprocessor, $\overline{W}_{10}$ is computed from the ERA5 wind components as $(U_{10}^2 + V_{10}^2)^{1/2}$ before the urban roughness rescaling, because the formulation of Theeuwes et al. (2016) is based on wind speed in non-urban surroundings rather than on canopy-reduced urban wind. The intra-night evolution is prescribed using an asymmetric sine-shaped function whose timing follows observed UHI
270 behavior. Rather than using fixed clock times, the night window is diagnosed directly from ERA5 shortwave radiation ~~it~~ extends from the ~~night~~. Night is defined as the period around the daily zero-shortwave interval, extended from four hours before $\text{SWDOWN} = 0$ until the first two hours with $\text{SWDOWN} > 0$ after sunrise. Within this night window, the additive perturbation applied to air temperature is

$$\text{UHI}_{d,L}(t, x, y) = \begin{cases} [2 - \text{SVF}(x, y) - f_{\text{veg}}(x, y)] \text{UHI}_{\max}(d) \sin\left(\pi \frac{s(t)}{L}\right), & t \in \text{night window}, \\ 0, & \text{daytime.} \end{cases} \quad (2)$$

275 where $\text{SVF}(x, y)$ is the sky-view factor used for the UHI modulation, $f_{\text{veg}}(x, y)$ the vegetation fraction is a local vegetation indicator on the common SOLWEIG grid, $s(t)$ is the elapsed time since the night-window start, and L its duration. The SVF is computed from buildings, terrain, and tree-canopy obstructions simultaneously; low-lying vegetation is not included in the SVF because it does not obstruct the sky at pedestrian level. In the Dortmund implementation, $f_{\text{veg}} = 1$ for tree-canopy cells and vegetated land-use cells, and $f_{\text{veg}} = 0$ for built, water, and bare cells.

280 The modulation term $(2 - \text{SVF} - f_{\text{veg}})$ is therefore a diagnostic, theory-guided proxy rather than a coefficient fitted to local observations or a fully parameterized vegetation-energy-balance scheme. It attenuates the applied UHI in open or highly vegetated areas, where nocturnal cooling is more effective. Directly using spatially and temporally varying modeled radiation and wind within the local UHI modulation would be more physically complete, and is therefore retained as a future extension.

~~This diagnostic~~ The resulting adjusted air-temperature field is evaluated and written on the same 2 m grid as the SOLWEIG radiative fields, because SOLWEIG requires co-registered meteorological inputs for each tile. This should be interpreted as a diagnostic downscaling of a city-scale daily UHI amplitude according to local morphology, not as a claim that atmospheric UHI variability is physically resolved at exactly 2 m. Coarser or spatially smoothed UHI fields remain a future sensitivity test.

This diagnostic scheme provides a computationally efficient way to introduce an approximate UHI effect—typically absent in ERA5 because of its coarse resolution and lack of an urban land-surface representation—while remaining compatible with the global, automated nature of the GLIDE-SOL workflow.

2.4.2 Elevation bias correction

Before forcing SOLWEIG, 2 m air temperature is adjusted ~~to from the ERA5 surface altitude to match~~ the local DEM height ~~through an effective, humidity-dependent lapse rate Γ_{eff} elevation~~. The height difference is defined as $\Delta H(x, y) = H_{\text{ERA5}} - H_{\text{DEM}}(x, y)$, so positive values correspond to terrain below the ERA5 surface and negative values to terrain above it. The implemented correction follows a parcel-based profile:

$$T_{2\text{m},\text{corr}}(x, y) = \mathcal{P}\left(T_{2\text{m}} + \Gamma_{\text{eff}} T_{2\text{m}}, p, \text{RH}, \Delta H(x, y)\right), \quad (3)$$

where p is air pressure, RH ~~relative humidity from the driving meteorology, and ΔH the height difference between the ERA5 surface altitude and~~ is relative humidity in percent, and $\mathcal{P}$ denotes the vertical temperature operator. For downward adjustment ($\Delta H > 0$), and for upward adjustment below the lifting condensation level (LCL), the ~~high-resolution DEM, expressed as $\Delta H = H_{\text{ERA5}} - H_{\text{DEM}}$. In the implementation, Γ_{eff} linearly interpolates between~~ profile follows the dry-adiabatic lapse rate $\Gamma_d = g/c_p \approx 9.8 \text{ K km}^{-1}$ and a moist-adiabatic lapse rate $\Gamma_m(T, p)$ computed from saturation specific humidity: $\Gamma_d = g/c_p \approx 9.8 \text{ K km}^{-1}$. For upward displacements, the LCL is diagnosed from T , p , and RH using a dew-point estimate following Bolton (1980) and the closed-form LCL expression of Roms (2017). Above the LCL, the saturated pseudo-adiabatic profile is integrated by coupling

$$\Gamma_{\text{eff}} \frac{dT}{dp} = \frac{(1 - \text{RH})\Gamma_d + \text{RH}\Gamma_m\left(T \frac{R_d T + L_v r_s}{p[c_p + L_v^2 r_s \epsilon / (R_d T^2)]}, p\right)}{p}, \quad (4)$$

~~Thus, the elevation correction smoothly transitions from dry to moist-adiabatic behavior depending on humidity, and with the hydrostatic relation~~

$$\frac{dp}{dz} = -\frac{pg}{R_d T_v}, \quad (5)$$

where r_s is the saturation mixing ratio, L_v the latent heat of vaporization, $\epsilon = R_d/R_v$, and T_v the virtual temperature. This correction is applied at every time step before computing T_{mrt} and UTCI ~~→~~, using the same formulation during daytime and night-time. We do not derive a time-varying lapse rate from ERA5 pressure-level or model-level fields in this implementation, because the objective is a lightweight forcing correction that can be applied consistently in the automated global workflow.

2.4.3 Wind reduction coefficients

We first harmonize the large-scale wind field from ERA5 and then derive directional, morphology-based wind reduction
315 coefficients $C(\mathbf{x}, \theta)$.

Reference wind

ERA5 provides near-surface wind components at 10 m height (U_{10}, V_{10}) together with a roughness length $z_{0, \text{ERA5}}$. The script estimates a domain-average urban roughness length $z_{0, \text{city}}$ from buildings and trees, and rescales the 10 m wind from $z_{0, \text{ERA5}}$ to $z_{0, \text{city}}$ assuming a neutral logarithmic wind profile. For each wind component we apply

$$320 \quad U_{10}^{\text{city}} = U_{10}^{\text{ERA5}} \frac{\ln(10/z_{0, \text{city}})}{\ln(10/z_{0, \text{ERA5}})}, \quad V_{10}^{\text{city}} = V_{10}^{\text{ERA5}} \frac{\ln(10/z_{0, \text{city}})}{\ln(10/z_{0, \text{ERA5}})}. \quad (6)$$

The resulting time series ($U_{10}^{\text{city}}(t), V_{10}^{\text{city}}(t)$) ~~represent~~ are used as a spatially uniform, domain-consistent background canopy wind. In SOLWEIG this background wind is later multiplied by the spatially varying coefficients $C(\mathbf{x}, \theta)$ described below.

Directional wake model

Directional wind-reduction coefficients $C(\mathbf{x}, \theta)$ are computed with a simplified , one-step version of the Röckle wake model
325 (Röckle, 1990; Bernard et al., 2023). The resulting flow is not mass balanced and should therefore be interpreted as a diagnostic attenuation field, not as a dynamically complete wind simulation. For each wind direction θ (12 directions with 30° spacing), the building and tree fields are rotated into wind-aligned coordinates so that the flow effectively comes from west. In this rotated grid, each connected building (or tree cluster) is characterized by an effective obstacle width W , depth D (along-wind), and height H . Here W and D are the dimensions of the obstacle's axis-aligned bounding box in the wind-aligned
330 coordinate system, and H is the mean positive rasterized building or canopy height inside the connected component. These dimensions are then used to define upwind and leeward zones. For compactness, the detailed side-by-side comparison with the full Röckle/URock methodology is reported in Appendix A.

Vertical uniformity assumption

In the present implementation, the upwind deceleration and leeward wake formulations are applied assuming that the wind
335 reduction coefficient is vertically uniform from the ground up to the obstacle height, i.e. up to the building height or the canopy top in the case of trees. ~~In other words, within the upwind and wake regions, the wind speed is assumed to be reduced by the same factor at all heights below the obstacle top, while the height dependence of the wind profile is only accounted for locally at the obstacle location (through the canopy flow parameterization for trees).~~ The reduction is also uniform across each affected obstacle column in the wind-aligned lateral direction before the final smoothing step. This differs from Röckle/URock
340 implementations that use ellipsoidal or otherwise tapered shapes in the lateral and vertical directions .

This assumption is consistent with the conceptual framework of simplified urban wake models, where the dominant effect of buildings and vegetation on the mean flow is represented through vertically integrated drag and displacement effects rather than

through a fully resolved vertical structure, especially in dense urban canopies. Several studies have shown that, for practical urban-scale applications, the bulk momentum deficit induced by buildings and canopies can be reasonably approximated as
 345 vertically homogeneous within the roughness sub-layer, up to the obstacle height (Santiago and Martilli, 2010; Cheng and Porté-Agel, 2015; Zonato et al., 2023). Given the objectives of the present study and the spatial resolution considered, this simplification offers a robust compromise between physical realism and computational efficiency.

Upwind deceleration

Upwind of each obstacle, the model prescribes a monotonic ramp from full wind to a reduced value over a characteristic ~~length~~
 350 displacement-zone length

$$L_f = \frac{2W}{1 + 0.8(W/H)} \frac{1.5W}{1 + 0.8(W/H)}. \quad (7)$$

We treat this upwind ramp as a pragmatic 2-D attenuation proxy rather than as a full Röckle displacement-zone geometry.

For buildings, the along-wind profile is parameterized as

$$C_f(x) = C_{\min} + (1 - C_{\min}) \left(\frac{x}{L_f} \right)^{p_f}, \quad 0 \leq x \leq L_f, \quad (8)$$

355 where x is the upwind distance from the wall (against the mean wind), $p_f = 1.5$, and $C_{\min} = 0.1$ is a lower bound enforced during post-processing. Very close to the building, C_f approaches $C_{\min}$, while farther upwind it gradually relaxes to 1.

Leeward wake

Downwind of buildings, the ~~wake-length~~ wake-zone length L_r ~~follows Röckle (1990):~~ is then set to three times the cavity length, following the Röckle/Kaplan–Dinar convention adopted in URock (Kaplan and Dinar, 1996; Bernard et al., 2023) :

$$360 \quad L_r = \frac{4 \times 1.8W}{\left(\frac{D}{H}\right)^{0.3} [1 + 0.24(\frac{D}{H})]} \frac{3 \times 1.8W}{\left(\frac{D}{H}\right)^{0.3} [1 + 0.24(\frac{D}{H})]}. \quad (9)$$

Along the wake centerline, the leeward recovery is assumed linear with distance:

$$C_b(x) = \frac{x}{L_r}, \quad 0 \leq x \leq L_r, \quad (10)$$

with $C_b(x)$ truncated to the range $[C_{\min}, 1]$ and $C_b \rightarrow 1$ as $x \rightarrow L_r$. Immediately downstream of the wall, C_b tends towards $C_{\min}$, representing the recirculation ~~and-vortex~~-zone. The implementation applies this recovery profile along each obstacle
 365 column in the wind-aligned grid, ~~while ensuring that overlapping wakes combine conservatively.~~ Where multiple building wakes overlap, their local reduction factors are multiplied and then clipped to $[C_{\min}, 1]$, so overlapping wakes strengthen attenuation without spuriously increasing wind speed.

Trees

Trees are treated with the same geometric description (W, D, H) , but as porous obstacles. This differs from URock, where
 370 vegetation drag is represented without adding the same building-like upwind and wake zones used here. The additional

upwind and leeward zones are a diagnostic GLIDE-SOL extension, motivated by the physical expectation that porous tree canopies induce upstream adjustment and coherent downstream wakes, as also shown in recent isolated-tree wake experiments (Grandoni et al., 2026). They should therefore be interpreted as a pragmatic first-order approximation rather than as a vegetation scheme formally validated within URock/Röckle. For each grid cell containing canopy, a local, height-dependent wind reduction

375 coefficient $C_{t,\text{base}}$ is first computed at the evaluation height ($z = 10$ m in this study) using a canopy-flow parameterization following Bernard et al. (2023). The model depends on an effective leaf area index

$$\text{LAI}_{\text{eff}} = \text{LAI} \lambda_p, \quad (11)$$

where LAI is the leaf area index (expressed as $\text{m}^2 \text{m}^{-2}$ and set to $\text{LAI} = 5$) and λ_p is the canopy plan-area fraction. In each grid cell, the canopy height H is taken from the tree DSM, and we define a displacement height $d = 0.7 H$ and a canopy roughness
380 length $z_{0,\text{tree}} = 0.1 H$, following standard canopy-flow parameterizations. The base attenuation coefficient k (denoted α in the implementation) is then modeled as

$$k = a_0 + a_1 \text{LAI}_{\text{eff}}. \quad (12)$$

~~With~~with $a_0 = 0.5$ and $a_1 = 0.2$. The base canopy reduction factor at height z is then defined piecewise. Let H be the local canopy height (from the tree DSM), $d = 0.7 H$ the displacement height, and $z_{0,\text{tree}} = 0.1 H$ the canopy roughness length (with
385 a small lower bound to avoid singularities). Denoting the reference roughness by $z_{0,\text{ERA5}}$ (taken from the meteorological dataset), we first define the reference neutral wind-profile denominator

$$D_{\text{ref}}(z) = \ln\left(\frac{z}{z_{0,\text{ERA5}}}\right), \quad (13)$$

and we bound the arguments of the logarithms in the numerator so that they remain larger than 1.

For points above or just at the canopy top ($z \geq H$), the base reduction factor is purely logarithmic:

$$390 \quad C_{t,\text{base}}(z \geq H) = \frac{\ln((z - d)/z_{0,\text{tree}})}{D_{\text{ref}}(z)}. \quad (14)$$

For points inside the canopy ($z < H$), the model assumes that the wind speed at the canopy top follows the same logarithmic scaling, but decays exponentially towards the ground according to the attenuation coefficient k :

$$C_{t,\text{base}}(z < H) = \frac{\ln((H - d)/z_{0,\text{tree}})}{D_{\text{ref}}(z)} \exp\left[-k\left(1 - \frac{z}{H}\right)\right], \quad (15)$$

so that $C_{t,\text{base}} \rightarrow \ln((H - d)/z_{0,\text{tree}})/D_{\text{ref}}(z)$ at the canopy top ($z \rightarrow H$) and decreases towards $\exp(-k)$ near the ground.

395 Given $C_{t,\text{base}}$ at the obstacle location, we apply the same ~~wake geometry as for buildings, with an upwind deceleration over~~

$$L_f = \frac{2W}{1 + 0.8(W/H)}$$

~~and a leeward wake of length~~

$$L_r = \frac{4 \times 1.8 W}{\left(\frac{D}{H}\right)^{0.3} [1 + 0.24 \left(\frac{D}{H}\right)]}.$$

diagnostic wake geometry adopted for buildings. Accordingly, the upwind influence length L_f and the leeward wake length L_r are computed using Eqs. (7) and (9), respectively.

Upwind of the canopy edge (x measured against the mean wind), the coefficient is ramped from $C_{t,\text{base}}$ to 1 using the same functional ~~shape as for buildings,~~ form as Eq. (8).

$$C_{t,\text{up}}(x) = C_{t,\text{base}} + (1 - C_{t,\text{base}}) \left(\frac{x}{L_f} \right)^{p_f}, \quad 0 \leq x \leq L_f, \quad (16)$$

with ~~$p_f = 1.5$.~~ $p_f = 1.5$.

Downwind, the profile recovers linearly from $C_{t,\text{base}}$ ~~towards to~~ 1 over the wake length ~~L_r .~~

$$C_{t,\text{down}}(x) = C_{t,\text{base}} + \left(1 - C_{t,\text{base}} \right) \frac{x}{L_r}, \quad 0 \leq x \leq L_r. \quad (17)$$

Combination and smoothing

For each direction θ , building and tree wakes are computed on the wind-aligned grid and then rotated back to the original grid. Within each contribution, overlapping wake factors are multiplied and clipped to the prescribed coefficient range. At each grid point, ~~we combine the two contributions~~ the final building and tree contributions are then combined multiplicatively,

$$C(\mathbf{x}, \theta) = C_b(\mathbf{x}, \theta) C_t(\mathbf{x}, \theta), \quad (18)$$

~~with building interiors masked out.~~ The resulting 2-D field is first Gaussian-smoothed ~~(at a short spatial scale and then~~ with an effective kernel of about 40 m ~~)~~ to blend overlapping wakes and suppress blocky artifacts ~~caused by rasterized obstacle edges and directional rotation.~~ The 40 m value was selected as a small neighborhood-scale smoother rather than as a calibrated physical wake length. It also regularizes the simplified plan-view wake footprints because GLIDE-SOL does not prescribe an ellipsoidal lateral/vertical wake envelope as in fuller Röckle/URock implementations. Finally, $C(\mathbf{x}, \theta)$ is clipped to the interval $[C_{\min}, 1]$ and stored as WindCoeff_dirXXX.tif (one file per direction). In SOLWEIG, the ~~near-surface canopy~~ wind speed is obtained by multiplying the domain-consistent ~~10-m background~~ wind ($U_{10}^{\text{city}}, V_{10}^{\text{city}}$) by these directional coefficients $C(\mathbf{x}, \theta)$. For the computation of UTCI, a minimum wind speed of 0.5 m s^{-1} is imposed to avoid unrealistically low values.

2.5 Case study: Dortmund

The city of Dortmund ($51^\circ 30' N, 7^\circ 28' E$), Germany, was selected as a case study area due to the large city-wide urban biometeorological weather station network. Dortmund is located in the larger metropolitan Ruhr region and was selected as a case study area in the ICLEI Action Fund 2.0 with the Data2Resilience project, which supported the implementation of data-driven services to enhance the resilience to extreme heat. Following the approach in Freiburg, Germany (Plein et al., 2024), a large weather station network was deployed. It consists of 51 stations measuring air-temperature and relative humidity using a Decentlab DL-SHT35 sensor ~~in the manufacturer's small, naturally ventilated radiation shield,~~ as well as 25 additional stations equipped with biometeorological sensors, specifically a black globe temperature sensor (Decentlab DL-BLG with 125 mm diameter) and an all-in-one weather station sensor (Decentlab DL-ATM41), providing additional parameters besides

air temperature and relative humidity such as black globe temperature, downward shortwave radiation, wind speed and wind direction, and precipitation. The stations are located throughout the city and cover a wide variety of urban structures based on Local Climate Zones. Biometeorological stations are deliberately placed at locations of public interest, such as main squares, urban parks and districts with combined vulnerabilities, to enable the local government to assess the heat exposure and guide data-driven adaptation measures. With few exceptions, stations are mounted on lamp posts 3.3 m above ground and 50 cm away from the pole. The black globe sensor always faces south, and this way avoids shading by the pole. In some cases (seven in total) where this is not possible due to other obstructions, it is precisely documented in the metadata (Hüser et al., 2026), where also each station setup is carefully described. Measured raw data is transmitted by individual sensors every five minutes via LoRaWAN (Long Range Wide Area Network) and sensor data are then combined during postprocessing, allowing for computation of derived biometeorological parameters such as mean radiant temperature (T_{mrt}) following DIN EN ISO 7726:2021-03 (2021) and the common thermal comfort indices UTCI (Jendritzky et al., 2012), PET (Höppe, 1999) and heat index (HI) (Steadman, 1979; Rothfusz, 1990). The maximum allowed temporal offset between sensor measurements (black globe and all-in-one sensor) is 5 minutes, labeling the combined station-measurement with the all-in-one sensor's original timestamp since the expected response time of the black globe sensor is much slower. The black-globe-derived T_{mrt} measurements were not independently calibrated against 3-D net radiometers within this study; hence, no calibration correction was applied to the T_{mrt} observations.

For this study, observations and metadata from 25 stations (more than 250,000 valid station-hour records) were derived via the public API (Application Programming Interface) which provides near-realtime data (<https://api.data2resilience.de>). Station coordinates are provided in WGS84 by the API, and the Dortmund domain is defined in UTM 32N (EPSG:32632) at 2 m grid spacing, covering the urban core and adjacent districts (tens of km^2). Simulations span the period from 6 August 2024 to 31 December 2025. For station-level LCZ context, we use the field-based LCZ classes reported in the station metadata rather than LCZ values sampled from the global raster map, because the field assignment better represents the immediate surroundings of each sensor location. Two model configurations are evaluated: a baseline run driven by unmodified ERA5 forcing (`Sol_STD`) and a configuration that activates both the morphology-based wind correction and the diagnostic UHI cycle (`Sol_WC_UHI`).

3 Results

We report computational performance and output volume for the Dortmund case study, illustrate the spatial imprint of the wind and UHI diagnostics, and evaluate station-based skill using aggregate statistics, distributions, and temporal and seasonal thermal stress metrics.

3.1 Computational performance

To quantify the practical impact of GPU acceleration, we benchmarked a single-day GLIDE-SOL run over Dortmund on a reduced 3129×3113 grid (2 m spacing). Using one NVIDIA A100 (40 GB) GPU, the 24 h simulation (saving UTCI, T_{mrt} ,

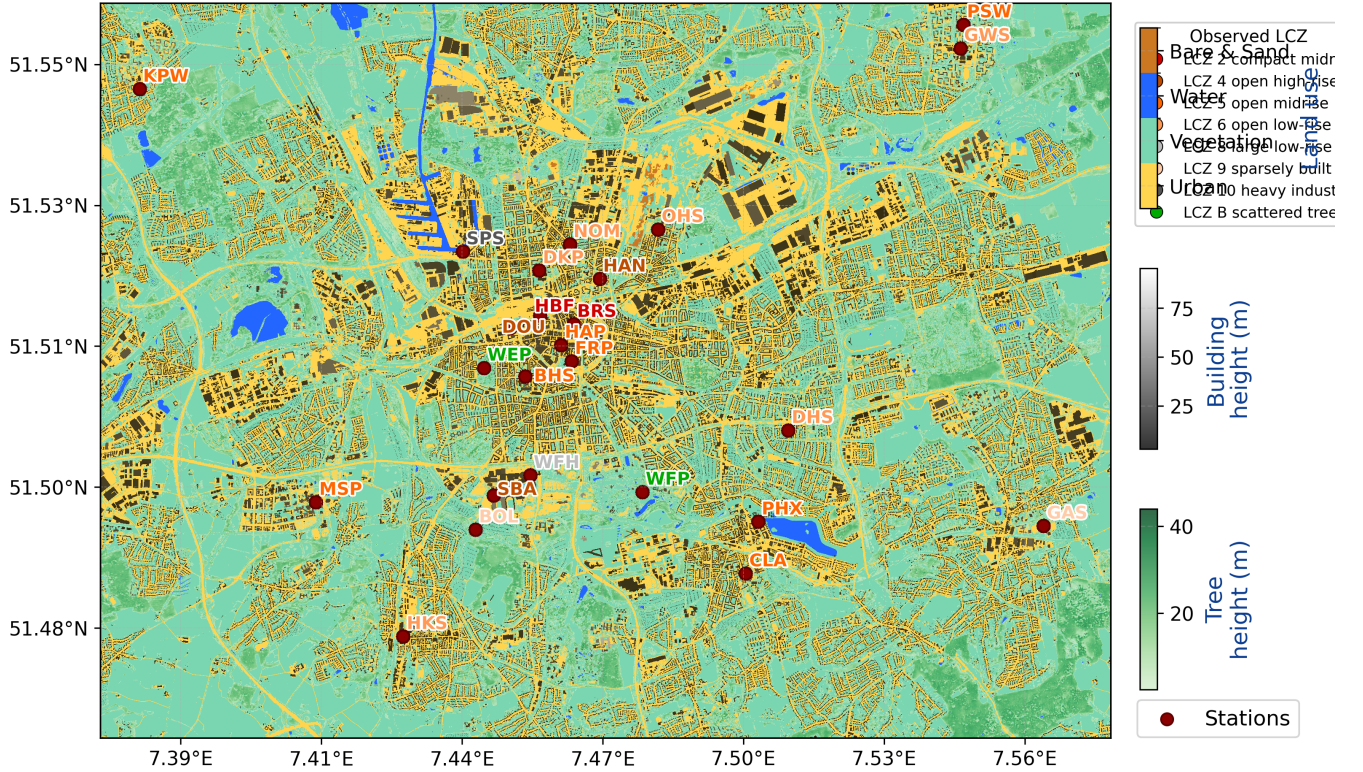


Figure 2. Dortmund model domain: land use, buildings, trees, and station points annotated with their respective ID on the common UTM32N grid. Generated during the input-build phase. [Station labels are colored according to the observed Local Climate Zone \(LCZ\) class reported in the station metadata, using the standard LCZ color scheme.](#)

Ta, and Va10m) completed in 254 s (10.6 s per simulated hour). The same configuration executed in CPU-only mode on the same node required 1285 s (53.5 s per simulated hour), corresponding to a wall-clock speed-up of about 5.1. For the GPU run, PyTorch CPU threading was restricted to `num_threads=1` to avoid host-side oversubscription; in CPU-only mode all logical CPU threads were available.

465 In addition to compute acceleration, deferred repacking to LERC+ZSTD reduces I/O and storage requirements. For the Dortmund case-study grid, an uncompressed daily UTCI stack would occupy about 3.3 GB, whereas the repacked GeoTIFF is 251 MB ($\sim 13\times$ smaller; 92 % reduction), using the compression error values described in 2.3.

3.2 Diagnostics of the wind and temperature corrections

The diagnostic wind module generates a directional attenuation coefficient field $C(\mathbf{x}, \theta)$ that converts the domain-consistent 10 m wind to a morphology-dependent ventilation proxy. For $\theta = 240^\circ$ (south-westerly flow; Fig. 3), C is lowest within dense blocks and in leeward wakes ($C \ll 1$), while major open corridors preserve higher effective wind speeds ($C \approx 1$). [Values close](#)

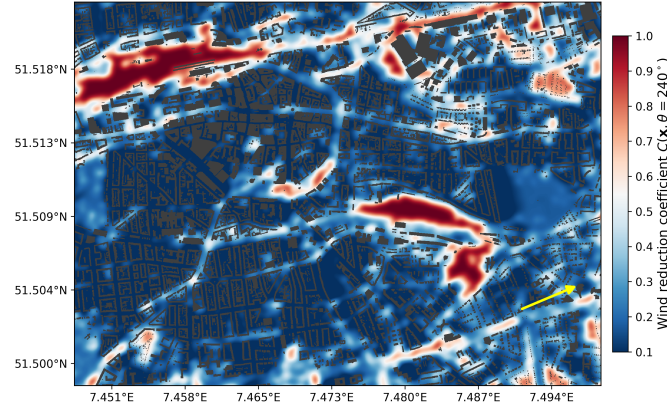


Figure 3. Example wind-reduction coefficient field $C(\mathbf{x}, \theta)$ for $\theta = 240^\circ$ (south-westerly flow) over Dortmund. Dark-blue regions indicate strong wind attenuation in dense urban fabric and in leeward wakes; ~~red regions~~ warm colors highlight ventilation corridors with limited reduction. The yellow arrow indicates the inflow direction used to compute upwind and downwind wakes.

to 1 should be interpreted as weak attenuation relative to the background wind rather than as explicit acceleration, because the model does not solve a mass-conserving flow field. Some smooth corridor-like structures in Fig. 3 therefore reflect the combination of wake overlap, rotation back to the native grid, and Gaussian smoothing, and local anomalies around individual
 475 buildings should be interpreted relative to the rasterized input geometry rather than as validated recirculation patterns. Although Reynolds-averaged and large-eddy CFD simulations provide higher-fidelity representations of shear layers and recirculation (Chu and Wang, 2025), the morphology-based $C(\mathbf{x}, \theta)$ provides a computationally inexpensive surrogate that retains the main anisotropy imposed by urban form. This is the physical mechanism by which the `Sol_WC_UHI` configuration compensates for the lack of explicit urban drag in coarse meteorological forcing.

480 The diagnostic UHI cycle acts on the background meteorological forcing rather than producing a standalone spatial field: it applies a night-time warming perturbation modulated by SVF and vegetation (Eq. 2). Its effect is therefore assessed through the station-based skill metrics and seasonal diagnostics presented below.

Figure 4 summarizes JJA mean fields from `Sol_WC_UHI` for central Dortmund. Station symbols report observed (left semicircle) and modeled (right semicircle) summer means at each location. Air temperature exhibits only modest spatial
 485 gradients and agrees well at station points. Wind speed shows strong morphology-driven heterogeneity, with low values in dense built-up areas and higher values in open corridors and peripheral zones; this pattern is consistent with the wake-based attenuation and with the improved wind-speed statistics (Sect. 3.3). T_{mrt} displays pronounced small-scale variability due to shading and land cover, and the remaining differences at station locations are consistent with the residual T_{mrt} errors in Table 1. UTCI integrates these drivers and shows close agreement of summer means at station points, indicating that the diagnostic
 490 corrections translate into realistic warm-season thermal-stress levels.

Sol_WC_UHI - JJA: model + station

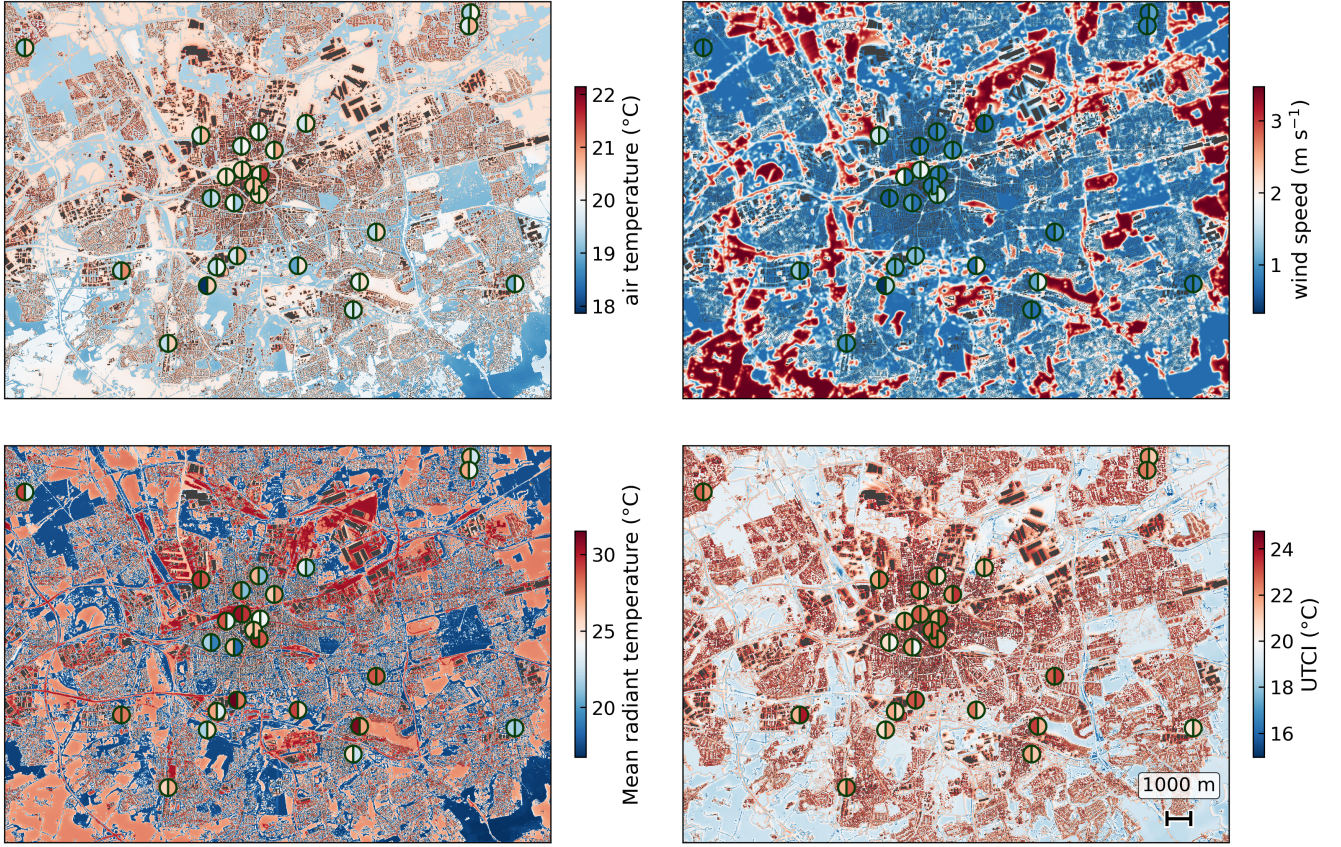


Figure 4. Summer (JJA) mean fields for the `Sol_WC_UHI` configuration. Panels show (top left) air temperature, (top right) wind speed, (bottom left) mean radiant temperature (T_{mrt}), and (bottom right) UTCI. Circles denote station locations; for each station, the left half of the symbol represents observed values, while the right half shows the corresponding modeled summer mean.

3.3 Aggregate skill across all stations

Model skill is evaluated against hourly measurements from 25 stations with heterogeneous but overlapping temporal coverage between August 2024 and December 2025 (more than 250,000 station-hour records). We compare two configurations: a baseline run driven by unmodified ERA5 meteorology (`Sol_STD`) and a run that activates the morphology-based wind correction and the diagnostic UHI cycle (`Sol_WC_UHI`). Table 1 summarizes the aggregate performance [against the station observations used in this paper](#). The combined corrections reduce the UTCI cold bias from -8.85 to -0.82 -7.07 to -0.85 °C and cut RMSE from 9.90 to 2.78 8.09 to 2.84 °C (7265 % reduction). Improvements are also evident for T_{mrt} (RMSE 7.34 6.91 °C $\rightarrow$ 6.24 6.29 °C) and canopy air temperature (RMSE 1.78 °C $\rightarrow$ 1.53 1.30 °C). The largest [dynamical](#) gain occurs

for ~~wind speed~~canopy wind speed V_{can} , where the strong positive bias in Sol_STD is ~~nearly~~largely removed (bias ~~2.87~~2.18
500 $\rightarrow$ ~~0.02~~0.03 m s^{-1} ; RMSE ~~3.32~~2.56 $\rightarrow$ ~~0.74~~0.77 m s^{-1}).

Table 1. Aggregate performance against observations. Bias, ~~MAE~~, and RMSE are in $^{\circ}\text{C}$ for UTCI/ T_{mrt} / T_{a} and in m s^{-1} for canopy wind speed V_{can} .

Variable–configuration	Bias	MAE -RMSE
UTCI – Sol_STD	-8.85 <u>-7.07</u>	8.94 <u>9.90</u> 8.09
UTCI – Sol_WC_UHI	-0.82 <u>-0.85</u>	2.14 <u>2.84</u> 2.78
T_{mrt} – Sol_STD	-4.74 <u>-3.86</u>	5.90 <u>7.34</u> 6.91
T_{mrt} – Sol_WC_UHI	-2.87 <u>-2.76</u>	4.38 <u>6.29</u> 6.24
T_{a} – Sol_STD	-1.00	1.37 -1.78
T_{a} – Sol_WC_UHI	0.16 <u>0.14</u>	1.10 <u>1.30</u> 1.53
V_{can} – Sol_STD	2.87 <u>2.18</u>	2.88 <u>3.32</u> 2.56
V_{can} – Sol_WC_UHI	0.02 <u>0.03</u>	0.53 <u>0.77</u> 0.74

The all-hour T_{a} statistics in Table 1 combine daytime and night-time conditions. This aggregation is useful for the overall UTCI evaluation, but it partly masks the mechanism of the diagnostic temperature correction: during daytime, T_{a} is affected primarily by ERA5 forcing and the elevation-based correction, whereas at night it is additionally affected by the UHI cycle.

~~Table B1~~ Figure 5 reports station-level UTCI errors (RMSE and mean bias, MB) for Sol_STD and Sol_WC_UHI, with
505 sites sorted by sky-view factor (SVF) as a compact proxy for local enclosure and radiative exposure. The figure provides a first visual stratification along an open-to-enclosed urban gradient, while the exact numeric values are retained in Appendix B. Differences between observed and modeled SVF at individual stations mainly reflect representativeness: the model samples a 2 m grid cell from globally derived building and vegetation data, whereas the observed SVF characterizes the exact sensor surroundings, including small trees and facade details that are not always present in the input rasters. Open-source morphology
510 datasets are also uncertain at this scale, especially for vegetation; discrepancies can therefore be larger in urban canyons with street trees or small vegetation elements where the local obstruction seen by the sensor differs from the rasterized building and vegetation layers. In Sol_STD, the mean bias is uniformly negative across the network (between ~~-6.8 and -10.0~~-5.4 and -8.4 $^{\circ}\text{C}$) and RMSE remains high (~~7.8–11.26~~2–9.4 $^{\circ}\text{C}$) across the full SVF range, indicating that uncorrected forcing dominates the error (in particular, excessive wind cooling). With Sol_WC_UHI, RMSE decreases at every station (~~2.1~~1.7–
515 ~~4.3~~5 $^{\circ}\text{C}$) and biases collapse towards zero (range ~~-3.1 to 1.9~~-3.7 to 1.6 $^{\circ}\text{C}$).

3.4 Scatter and distributional diagnostics

The scatter plots (Figs. 6 and 7) provide a compact view of systematic errors and conditional biases. For UTCI (Fig. 6), Sol_STD exhibits a pronounced cold bias, consistent with excessive convective cooling from overestimated winds and with

UTCI errors by station (sorted by SVF obs). Bold indicates lowest error for each station and metric. Station SVF obs SVF mod RMSE (°C) MB (°C) Sol_STD Sol_WC_UHI Sol_STD Sol_WC_UHI BHS 0.20 0.21 9.73 **2.85** -9.08 **-1.32** GAS 0.20 0.21 9.23 **2.17** -8.11 **-0.71** WEP 0.22 0.21 9.77 **2.09** -8.81 **-1.00** OHS 0.23 0.64 10.48 **2.18** -9.42 **-0.54** BRS 0.23 0.34 11.20 **2.13** -10.05 **-0.32** CLA 0.32 0.32 9.68 **2.52** -8.62 **-0.98** BOL 0.36 0.85 9.90 **3.74** -7.91 **-0.77** SBA 0.38 0.38 9.53 **2.59** -8.50 **-1.42** HAP 0.38 0.86 10.72 **3.44** -9.28 **-1.07** DKP 0.43 0.43 10.65 **2.83** -9.88 **-1.78** HKS 0.45 0.75 9.32 **2.55** -8.21 **0.31** DOU 0.46 0.43 8.71 **3.10** -7.66 **0.26** NOM 0.46 0.48 10.81 **3.37** -9.91 **-2.60** GWS 0.47 0.47 10.59 **2.98** -9.73 **-0.47** HAN 0.51 0.79 10.36 **2.69** -8.99 **-0.09** MSP 0.58 0.58 7.76 **3.23** -6.78 **1.93** PSW 0.62 0.61 10.69 **3.30** -9.57 **-1.99** WFP 0.64 0.90 9.76 **4.31** -8.89 **-3.21** DHS 0.64 0.87 10.15 **2.51** -9.01 **-0.90** KPW 0.65 0.65 10.27 **3.54** -9.40 **-0.49** WFH 0.65 0.65 9.17 **2.58** -8.34 **-0.28** FRP 0.66 0.92 9.00 **3.07** -8.04 **-1.15** HBF 0.71 0.93 9.93 **3.88** -8.89 **-2.54** SPS 0.71 0.78 8.93 **3.47** -7.70 **-1.55** PHX 0.71 0.95 10.26 **4.17** -9.27 **-3.12**

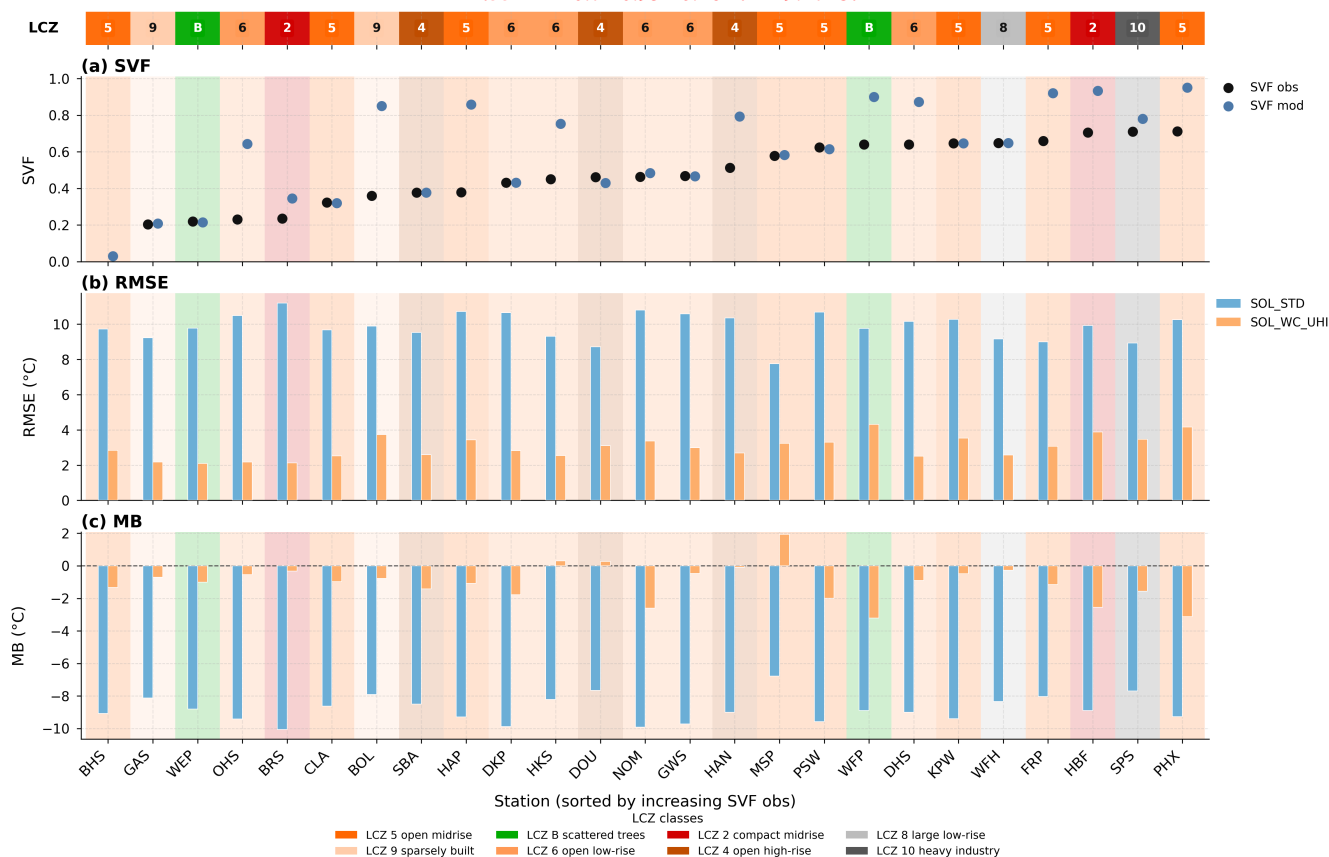


Figure 5. Station-level UTCI errors, sorted by observed SVF. Panels summarize RMSE and mean bias (MB) for *Sol_STD* and *Sol_WC_UHI* along the open-to-enclosed urban gradient; LCZ classes are shown as contextual descriptors of the observed station surroundings. Exact numeric values are reported in Appendix B.

missing nocturnal urban warming in the forcing. Activating wind attenuation and the UHI adjustment tightens the scatter and shifts the cloud towards the 1:1 line. In Fig. 7, the strongest improvement is in ~~wind-speed-(center)~~canopy wind speed V_{can} , where `Sol_WC_UHI` largely removes the positive bias. For canopy air temperature ~~(right), the UHI cycle reduces the cold bias and yields lower MAE/~~the correction reduces both bias and RMSE, while T_{mrt} ~~(left)~~ improves more modestly.

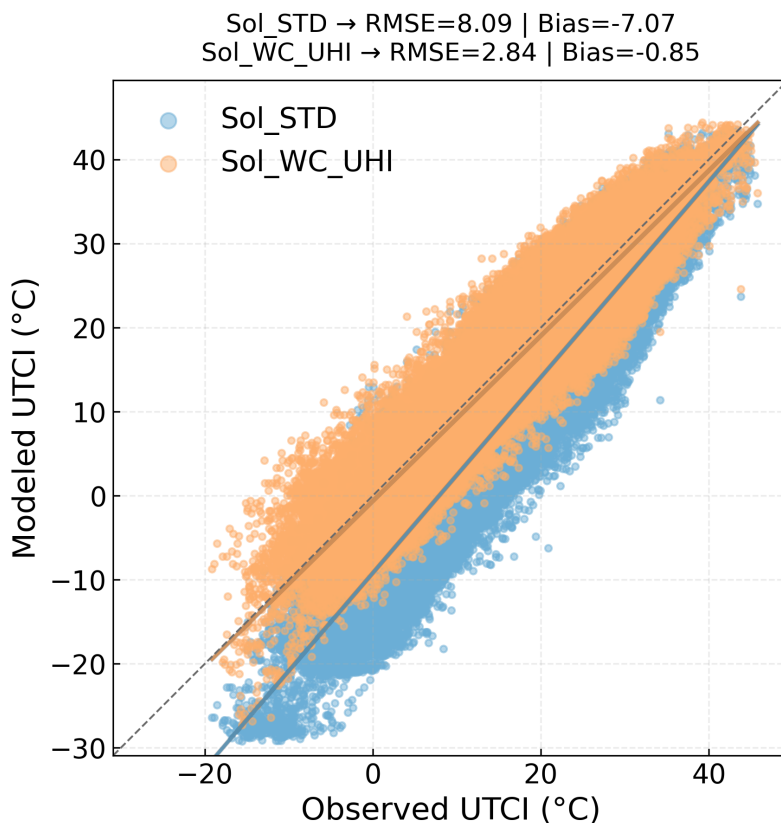


Figure 6. Observed vs. modeled UTCI for all stations and hours. The baseline `Sol_STD` ~~(red)~~ shows a systematic cold bias, whereas `Sol_WC_UHI` ~~(green)~~ concentrates closer to the 1:1 line, consistent with improved wind and temperature forcing.

The probability density functions (Fig. 8) provide a distribution-level evaluation of the main UTCI drivers and confirm that the corrections primarily act through wind and near-surface air temperature forcing.

For air temperature (top-left), both configurations reproduce the broad observed distribution, while `Sol_WC_UHI` shifts the PDF closer to the observations, consistent with the reduced T_a bias. The canopy wind speed V_{can} PDF (top-right) reveals the major deficiency of `Sol_STD`: a strong shift towards higher wind speeds and an unrealistically long high-wind tail (up to $\sim 10\text{--}12\text{ m s}^{-1}$). `Sol_WC_UHI` largely removes this artifact, recovering the observed low-wind peak and damping the tail.

Consistently, the UTCI PDF (bottom-left) in `Sol_STD` is shifted towards lower values and exhibits an amplified cold tail, while `Sol_WC_UHI` moves the distribution back towards the observed mode and reduces the spurious cold tail. In contrast, T_{mrt}

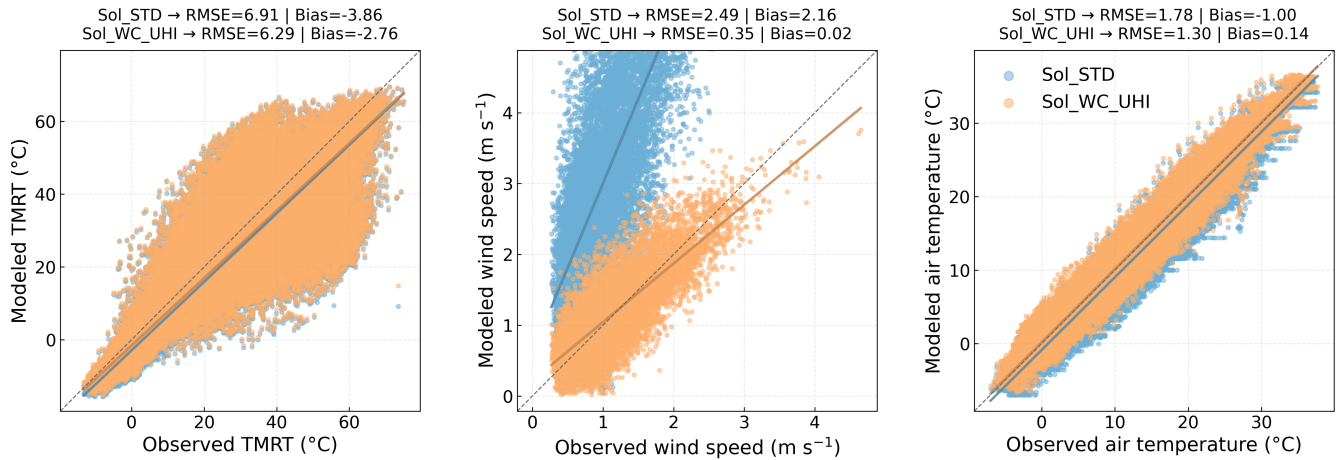


Figure 7. Observed vs. modeled (left) T_{mrt} , (center) [canopy](#) wind speed V_{can} , and (right) air temperature for all stations and hours. The baseline run (Sol_STD; labeled Sol_STD in the panel titles) shows large wind-speed overestimation and a cold bias in T_a , while the diagnostic wind and UHI corrections in Sol_WC_UHI reduce bias and RMSE, particularly for [wind-speed](#) V_{can} .

PDFs (bottom-right) show only limited sensitivity to the applied corrections, indicating that remaining errors are dominated by radiative forcing, surface properties, and input uncertainties rather than by aerodynamic exposure.

3.5 Temporal behavior and thermal stress categories

To assess whether the improvements are persistent rather than limited to mean statistics, we examine the temporal evolution of spatially averaged conditions across all stations (Figs. 9 and 10) and the resulting UTCI category frequencies (Fig. 11). Because the series are aggregated over the entire station network, they primarily reflect synoptic-to-seasonal variability, so remaining offsets or amplitude errors indicate systematic bias.

The [wind-speed](#) V_{can} time series (Fig. 9) highlights the dominant deficiency of the baseline configuration (Sol_STD, ERA5-driven winds without local urban diagnostics): winds are systematically too strong for the urban canopy and exhibit frequent high-wind excursions that are not present in the observations. In Sol_STD, wind speeds repeatedly spike above $\sim 8\text{--}12\text{ m s}^{-1}$, whereas observed winds at the station network remain mostly below $\sim 2\text{ m s}^{-1}$. The combined roughness rescaling and wake-based attenuation in Sol_WC_UHI suppress these excursions and constrain simulated winds to the observed envelope while preserving synoptic variability. This correction is critical because UTCI is highly sensitive to near-surface wind under cold and moderate conditions.

Consistent with the wind behavior, the UTCI time series (Fig. 10) shows a persistent cold bias in Sol_STD throughout the evaluation period, including exaggerated negative excursions during cold-season outbreaks and damped summer peaks. The corrected configuration Sol_WC_UHI substantially reduces this offset and reproduces the seasonal progression and much of the event-to-event variability. Periods of largest disagreement in Sol_STD coincide with intervals of excessive winds in Fig. 9,

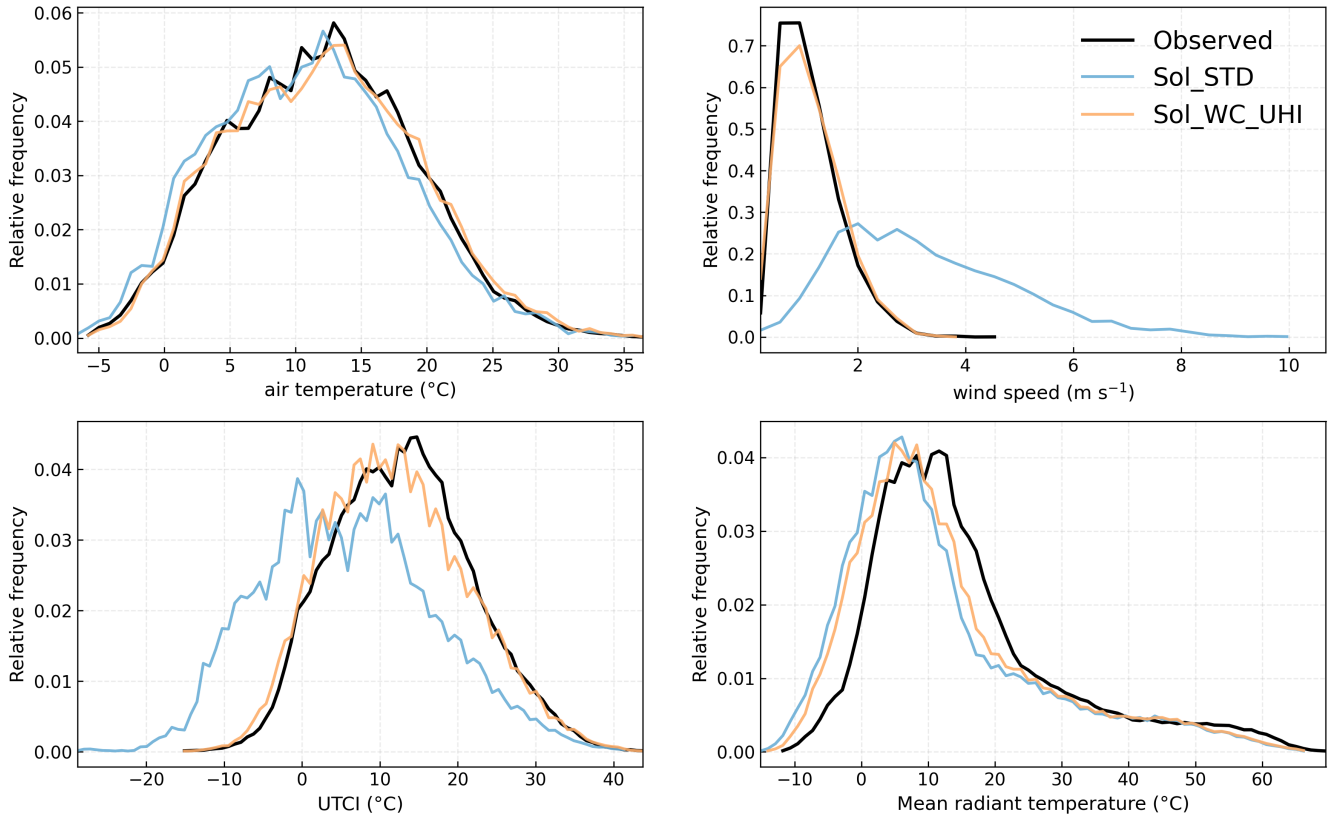


Figure 8. Probability density functions for canopy air temperature, [canopy](#) wind speed V_{can} , UTCI, and T_{mrt} . Model curves are compared with observations (black). The combined wind and UHI corrections in Sol_WC_UHI suppress the spurious high-wind tail and remove most of the UTCI cold shift present in Sol_STD.

indicating that unrealistic aerodynamic exposure to ERA5 winds is a key driver of the baseline UTCI bias. The nocturnal UHI
550 adjustment provides an additional contribution under stable night-time conditions.

The improved continuous UTCI signal translates into a more realistic partitioning into thermal stress categories (Fig. 11). In the baseline case, the systematic cold shift redistributes hours from “no thermal stress” into cold-stress classes: Sol_STD overestimates moderate and strong cold stress by + ~~25.5%~~23.1 and + ~~6.2%~~2.5 percentage points, and underestimates “no thermal stress” by ~~-26.8%~~-22.5 percentage points. With Sol_WC_UHI, category biases are within a few percentage
555 points across the spectrum (e.g., slight cold stress + ~~2.7%~~2.8 percentage points, moderate cold stress + ~~1.7%~~2.0 percentage points, and no thermal stress ~~-4.3%~~-4.6 percentage points), and warm-season heat stress frequencies align closely with the observations. Beyond station-based aggregation, the impact of the diagnostics is reflected in the spatial mapping of category frequencies across the Dortmund domain (Figs. 12 and 13), which determines where cold and heat stress exposure accumulates.

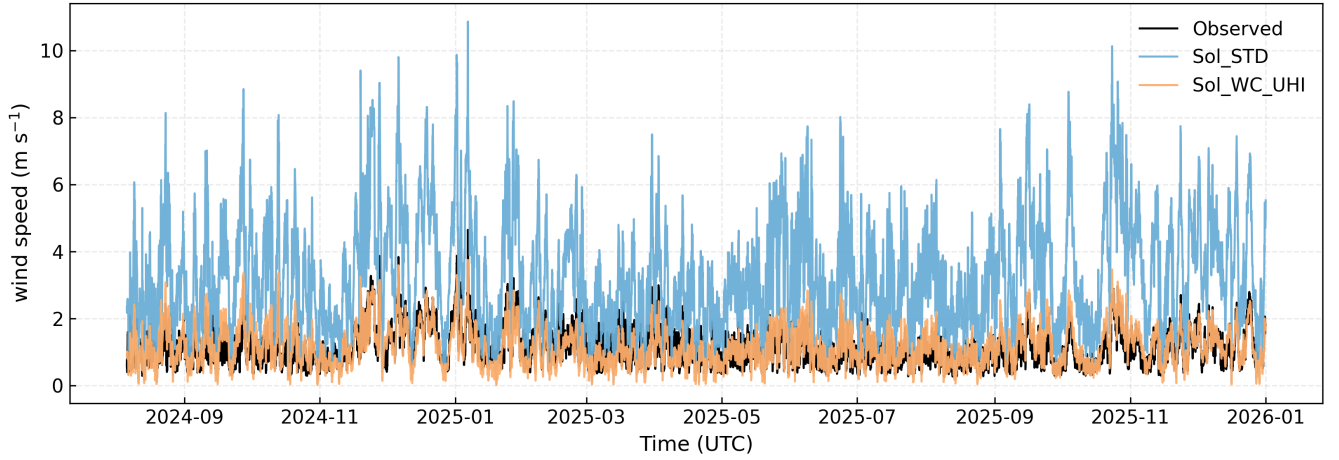


Figure 9. Time series of spatially averaged canopy wind speed V_{can} over all stations. The baseline Sol_STD shows frequent unrealistically high winds, whereas Sol_WC_UHI largely aligns with observed magnitudes after roughness rescaling and wake-based attenuation.

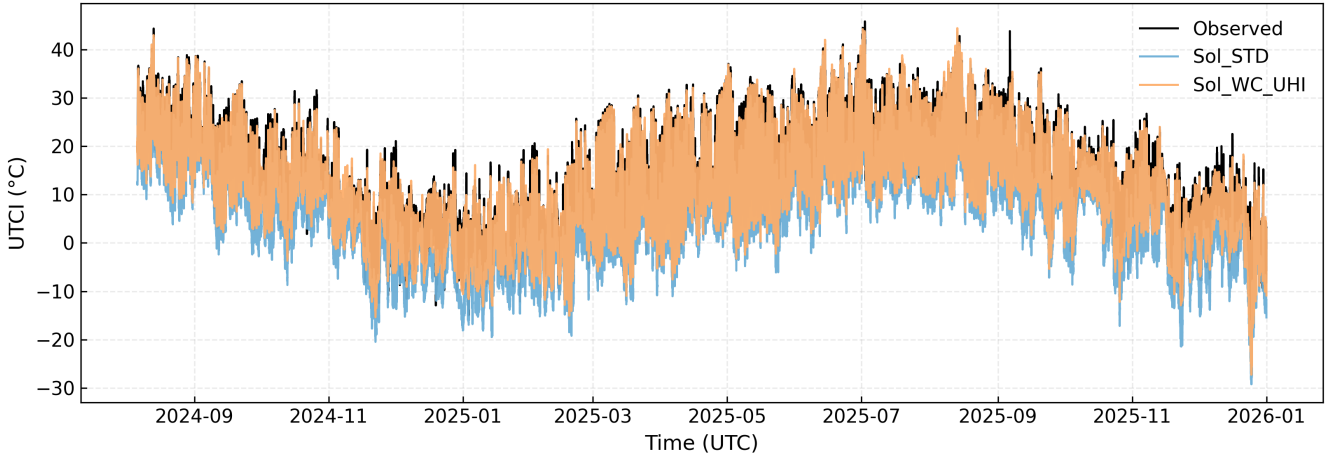


Figure 10. Time series of spatially averaged UTCI over all stations. Sol_STD remains systematically colder than observations, while Sol_WC_UHI reduces the offset and better reproduces the seasonal cycle and event-to-event variability.

560 In winter (DJF), the fraction of hours in the “slight cold stress” category (0–9 °C UTCI) provides a sensitive diagnostic of the model’s cold shift: if UTCI is systematically underestimated, hours are redistributed from this intermediate class into moderate and strong cold-stress categories. Figure 12 shows that Sol_STD assigns uniformly low fractions across the domain, masking the expected center-to-periphery contrast. With Sol_WC_UHI, a clear urban-core signal emerges, with higher slight-cold frequencies over dense city fabric and lower values over parks, open areas, and the peri-urban fringe where ventilation is
565 stronger. Station symbols reinforce this pattern, with inner-city sites moving toward observed frequencies while peripheral sites

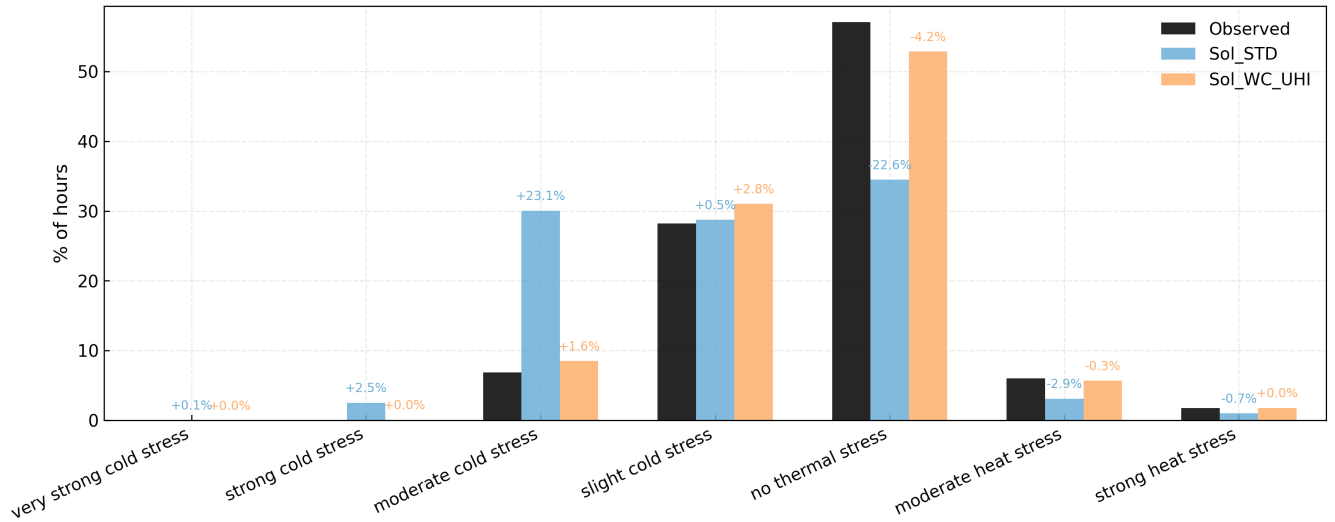


Figure 11. Hours per UTCI category across all stations. Bars show observed and simulated fractions; numbers above model bars indicate model–observation differences in percentage points. *Sol_WC_UHI* markedly improves the category distribution relative to *Sol_STD*, particularly by reducing spurious cold-stress frequencies and restoring the observed dominance of “no thermal stress”.

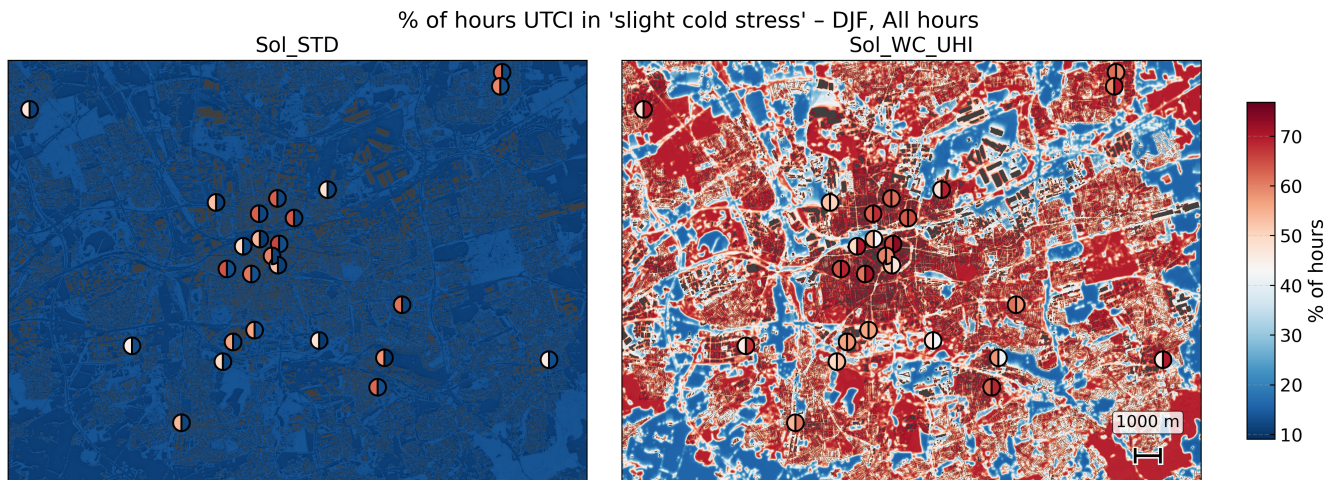


Figure 12. Fraction of hours classified as “slight cold stress” (UTCI) in DJF, considering all hours. Left: *Sol_STD*. Right: *Sol_WC_UHI*. Circles denote station locations; for each station, the left half of the symbol represents observed frequencies, while the right half shows the corresponding model value.

retain lower fractions. In summer (JJA), “moderate heat stress” (26–32 °C UTCI) shows a strong spatial contrast tied to urban form and ventilation (Fig. 13). In *Sol_STD*, moderate heat-stress frequencies are muted and relatively flat, consistent with the tendency to damp warm-season stress through excessive wind speeds even in dense neighborhoods. With *Sol_WC_UHI*,

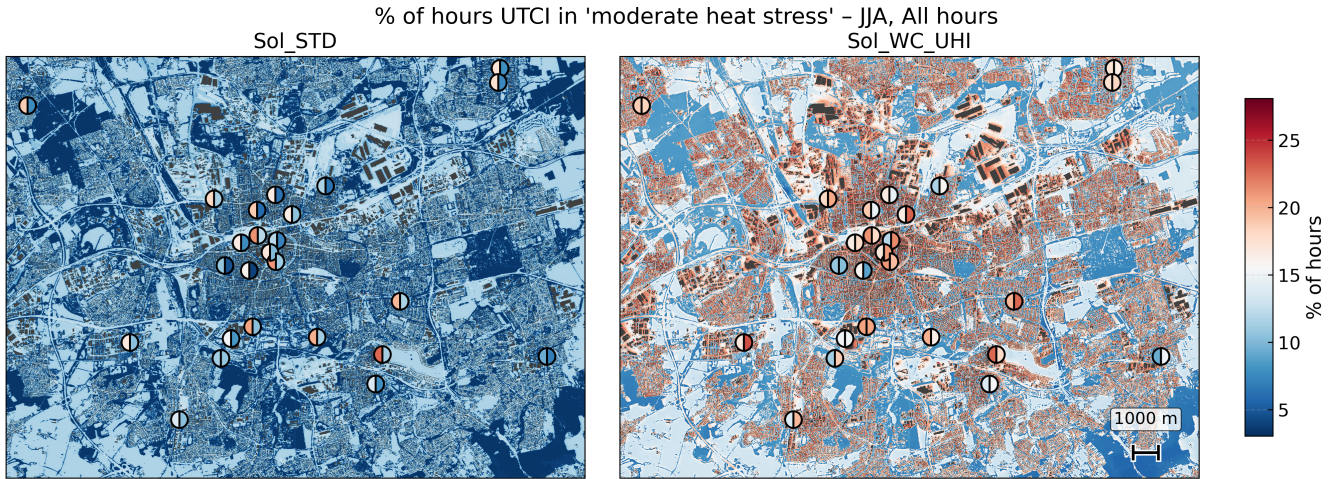


Figure 13. Fraction of hours classified as “moderate heat stress” (UTCI) in JJA, considering all hours. Left: Sol_STD. Right: Sol_WC_UHI. Circles denote station locations; for each station, the left half of the symbol represents observed frequencies, while the right half shows the corresponding model value.

a center-to-outskirts gradient becomes visible: higher fractions emerge over compact, wind-sheltered urban fabric and heavily built corridors, while parks, green areas, and the outer suburban fringe retain low values. Station symbols indicate that the corrected configuration better captures both the elevated inner-city frequencies and the lower peripheral values without overstating the overall occurrence.

4 Discussion

The Dortmund evaluation demonstrates that two lightweight diagnostics—directional wind attenuation and a nocturnal UHI adjustment—substantially reduce the cold bias that arises when SOLWEIG is forced directly with coarse reanalysis fields. In the baseline configuration (Sol_STD), near-surface winds are too strong for the urban canopy and night-time air temperature is underestimated, producing a persistent cold offset and an exaggerated cold tail in UTCI (Figs. 10 and 8). The temporal and category analyses indicate that the corrections improve not only mean skill but also event-scale variability and the partitioning of hours into cold- and heat-stress classes, which is essential for exposure assessments. Because the workflow is driven by globally available inputs and standardized preprocessing, these gains are achieved without bespoke local data assembly, supporting consistent multi-city applications.

The wind diagnostic is the dominant contributor to the UTCI improvement. By imprinting building and tree morphology onto the canopy wind through the coefficient fields $C(\mathbf{x}, \theta)$ (Fig. 3), Sol_WC_UHI removes the spurious high-wind tail (Fig. 8) and nearly eliminates the wind-speed bias (Table 1), consistent with Röckle-style conceptualizations of urban flow (Röckle, 1990). The resulting spatial gradients align with dense urban cores and more ventilated outskirts, reinforcing the physical consistency

of the approach. The remaining station-to-station spread suggests that unresolved local exposure and representativeness (e.g., site-specific shielding) still matter, but to a much lesser extent than the forcing bias.

The diagnostic UHI cycle provides a complementary correction that is most relevant under stable nocturnal conditions, particularly in winter. It shifts the distributions of air temperature and UTCI towards the observations and reduces extreme cold-stress episodes (Figs. 8 and 10). Its simple structure keeps computational cost low and enables consistent application across regions, but the residual positive T_a bias in `SOL_WC_UHI` (Table 1) indicates that a single diagnostic parameter set cannot capture the full range of synoptic regimes and advective effects; incorporating flow-dependent predictors is a promising avenue for future development. Wind is the dominant contributor to the all-hour UTCI improvement, while future work should further improve the reproduction of air temperature.

T_{mrt} improvements are comparatively modest (Table 1; Figs. 7 and 8), consistent with T_{mrt} being driven primarily by radiative forcing and urban geometry. Because the Dortmund simulations use the SOLWEIG v2022a anisotropic diffuse-shortwave and longwave sky schemes (Wallenberg et al., 2020, 2023), the remaining T_{mrt} bias cannot be attributed simply to an omitted isotropic-sky approximation. Air temperature (T_a) influences T_{mrt} mostly indirectly: it modulates atmospheric longwave emission (through sky emissivity) and, in SOLWEIG, it is used to parameterize surrounding surface temperatures, including wall temperature (T_{wall}), which in turn affects the longwave radiation received by the pedestrian. Remaining discrepancies likely reflect uncertainties in morphology and surface properties and missing processes such as anthropogenic heat and its effect on surface temperatures and long-wave emission, especially during the heating season (Liu et al., 2023; Wallenberg et al., 2025). In a global context, improving canopy and surface characterization layers is therefore a key path to further gains in radiative skill.

The T_{mrt} observations should also be interpreted in the context of the measurement setup. In the Dortmund network, T_{mrt} is derived from black-globe temperature and accompanying meteorological measurements following DIN EN ISO 7726:2021-03 (2021) using Decentlab DL-BLG sensors. These observations were not calibrated in this study against 3-D net radiometers, so no calibration-based adjustment was applied before model evaluation.

From a modeling and reproducibility standpoint, GLIDE-SOL addresses scalability constraints that often limit city-scale, meter-scale applications. GPU acceleration reduces wall-clock time by about a factor of five for the Dortmund benchmark. Deferred LERC+ZSTD repacking reduces output volumes by about 92 % while enforcing explicit error budgets per variable, producing lightweight GeoTIFF archives that reduce I/O and storage pressure. Together with the global input pipeline, these features enable multi-year, city-scale UTCI mapping without prohibitive compute or storage requirements and make coordinated multi-city experiments operationally feasible.

Limitations of the present demonstration include uncertainty in open building and tree-height products, a simplified diagnostic representation of urban heat storage, and reliance on coarse ERA5 forcing that omits mesoscale circulations and city-wide advection (Kittner et al., 2025). Additional limitations are the absence of an urban modification to relative humidity, the lack of anthropogenic heat contributions from building heating/cooling and traffic, and the use of a simplified urban wind-reduction model that cannot fully capture local channeling or sheltering →, does not enforce mass conservation, and does not include terrain-following wind coordinates. Several numerical choices in the current wind implementation—including the number

of wind sectors, the wake-length multipliers, and the Gaussian smoothing length—were selected pragmatically for robustness and computational efficiency rather than calibrated independently. Future work should therefore evaluate the diagnostics across multiple cities and climates, quantify sensitivity to morphology and roughness assumptions, ~~and test alternative directional and smoothing settings, perform component-ablation experiments for wind, elevation, and UHI corrections, and~~ explore coupling the UHI signal to mesoscale predictors ~~or~~, modeled radiation and wind, urban canopy schemes, or terrain-aware diagnostic wind formulations such as terrain-following QUIC-URB/QUIC-Fire coordinate systems (Robinson et al., 2023), with attention to regional variability in global input quality.

5 Conclusions

GLIDE-SOL extends SOLWEIG into a scripted, globally deployable workflow that (i) builds the full set of SOLWEIG inputs from global data sources with standardized preprocessing, (ii) adds computationally cheap diagnostics to mitigate known biases in coarse meteorological forcing over cities, and (iii) enables scalable simulations through GPU acceleration and bounded-error output compression that yields lightweight GeoTIFF archives for long-term analyses. The automated data-engine and configuration-driven pipeline are key novelties that make city-scale UTCI mapping reproducible and transferable without bespoke local datasets.

For Dortmund (25 stations; more than 250,000 station-hour records), the enhanced configuration `Sol_WC_UHI` reduces UTCI RMSE from ~~9.90 to 2.78~~ 8.09 to 2.84 °C and the mean bias from ~~-8.03 to -0.55~~ -7.07 to -0.85 °C. The improvement is driven primarily by correcting the wind speed (bias ~~2.87 to 2.18~~ 0.02 to 0.03 m s⁻¹), with additional gains from the nocturnal UHI adjustment. Beyond mean skill, the corrections restore the temporal evolution of UTCI, reduce spurious cold-stress hours, and recover realistic spatial contrasts in winter cold stress and summer heat-stress hotspots, indicating that globally driven diagnostics can reproduce both temporal and spatial exposure signatures.

On the technical side, a 24 h benchmark on a 3129 × 3113 grid completes in 254 s on a single NVIDIA A100 GPU (about 5× faster than CPU-only), and daily outputs can be reduced by over 90 % using LERC+ZSTD with explicit error budgets. The combination of fast GPU execution and lightweight GeoTIFF storage supports routine, meter-resolution UTCI mapping at city scale over multi-year periods, enabling consistent multi-city benchmarking, scenario testing, and evaluation of heat-mitigation strategies at regional to global scales.

Code and data availability

The GLIDE-SOL source code is archived on Zenodo (Zonato et al., 2026) and is available at <https://doi.org/10.5281/zenodo.18671813>. The Zenodo archive provides a citable release, while ongoing user support, bug reports, and community interaction are intended to be handled through the associated public code repository and issue tracker. The observational dataset used for the Dortmund evaluation is available on Zenodo at <https://zenodo.org/records/18221203>. The GPU implementation draws on

the open-source SOLWEIG-GPU project ~~-, available at~~ [and the implementations discussed in this paper are also available at https://github.com/nvnsudharsan/SOLWEIG-GPU/tree/main.](https://github.com/nvnsudharsan/SOLWEIG-GPU/tree/main)

Author contributions

A.Z. developed and integrated the GLIDE-SOL workflow, implemented the software, conducted the computational experiments, and wrote the original draft. M.D. contributed to the conceptualization and methodology and co-developed the software and experiments. H.G.K. and N.S. contributed to the GPU and software implementation and supported the computational experiments. L.M. contributed to the software and workflow implementation and supported the computational experiments. J.K. and L.W. contributed to the methodology and paper organization, curated and processed the observational datasets, contributed to the analysis, and contributed substantially to the writing of the text and figures. B.B. contributed to the curation and processing of the observational datasets. A.M. and M.M. contributed to the interpretation of the results and the revision of the manuscript. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

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Appendix A: [Wind-model comparison](#)

Appendix B: [Station-level UTCI errors](#)

Table A1. Comparison between the diagnostic wind treatment implemented in GLIDE-SOL and the full Röckle/URock methodology.

<u>Model component</u>	<u>URock (Röckle-based)</u>	<u>GLIDE-SOL</u>
<u>Wind directions</u>	<u>Continuous wind direction through domain rotation and geometry transformation</u>	<u>12 precomputed wind sectors (30° spacing).</u>
<u>Flow solution</u>	<u>Initial empirical wind field followed by an iterative mass-conservation solver</u>	<u>Single-pass attenuation model; no mass-conservation correction.</u>
<u>Building wake geometry</u>	<u>3-D Röckle zones with ellipsoidal displacement, cavity, wake, rooftop and corner regions</u>	<u>Only upwind and leeward attenuation along the wind-aligned x direction; no explicit 3-D wake geometry.</u>
<u>Zone interactions</u>	<u>Explicit treatment of overlapping Röckle zones, backward wakes and priority rules</u>	<u>Overlapping reductions combined through raster operations and Gaussian smoothing.</u>
<u>Street canyons</u>	<u>Explicit street-canyon circulation model</u>	<u>Not represented.</u>
<u>Vegetation</u>	<u>Dedicated vegetation zones (open and built-up canopies) with specific wind-factor formulations</u>	<u>Vegetation treated as porous obstacles with canopy attenuation and building-like upwind/leeward influence zones.</u>
<u>Terrain</u>	<u>No terrain-following coordinate transformation.</u>	<u>No terrain-following coordinate transformation.</u>
<u>Computational cost</u>	<u>3-D voxel model with iterative solver</u>	<u>2-D raster diagnostic model designed for fast computation.</u>

Table B1. UTCI errors by station (sorted by SVF obs). LCZ classes are taken from the field-based station metadata and are reported here as contextual descriptors of the observed station surroundings. Bold indicates lowest error for each station and metric.

<u>Station</u>	<u>LCZ</u>	<u>SVF obs</u>	<u>SVF mod</u>	<u>RMSE (°C)</u>		<u>MB (°C)</u>	
				<u>Sol_STD</u>	<u>Sol_WC_UHI</u>	<u>Sol_STD</u>	<u>Sol_WC_UHI</u>
<u>BHS</u>	<u>5</u>	<u>~</u>	<u>0.03</u>	<u>8.09</u>	<u>2.82</u>	<u>-7.51</u>	<u>-0.86</u>
<u>GAS</u>	<u>9</u>	<u>0.20</u>	<u>0.20</u>	<u>7.85</u>	<u>2.27</u>	<u>-6.92</u>	<u>-1.02</u>
<u>WEP</u>	<u>B</u>	<u>0.22</u>	<u>0.43</u>	<u>8.18</u>	<u>2.11</u>	<u>-7.30</u>	<u>-0.60</u>
<u>OHS</u>	<u>6</u>	<u>0.23</u>	<u>0.64</u>	<u>8.67</u>	<u>2.63</u>	<u>-7.56</u>	<u>-1.06</u>
<u>BRS</u>	<u>2</u>	<u>0.23</u>	<u>0.34</u>	<u>9.43</u>	<u>1.70</u>	<u>-8.37</u>	<u>-0.24</u>
<u>CLA</u>	<u>5</u>	<u>0.32</u>	<u>0.33</u>	<u>8.16</u>	<u>2.28</u>	<u>-7.37</u>	<u>-0.97</u>
<u>BOL</u>	<u>9</u>	<u>0.36</u>	<u>0.34</u>	<u>8.17</u>	<u>3.16</u>	<u>-6.61</u>	<u>-1.48</u>
<u>SBA</u>	<u>4</u>	<u>0.38</u>	<u>0.70</u>	<u>7.73</u>	<u>2.11</u>	<u>-6.57</u>	<u>-0.06</u>
<u>HAP</u>	<u>5</u>	<u>0.38</u>	<u>0.86</u>	<u>8.84</u>	<u>3.44</u>	<u>-7.42</u>	<u>-1.06</u>
<u>DKP</u>	<u>6</u>	<u>0.43</u>	<u>0.43</u>	<u>8.73</u>	<u>2.53</u>	<u>-8.04</u>	<u>-1.22</u>
<u>HKS</u>	<u>6</u>	<u>0.45</u>	<u>0.75</u>	<u>7.40</u>	<u>2.48</u>	<u>-6.31</u>	<u>0.14</u>
<u>DOU</u>	<u>4</u>	<u>0.46</u>	<u>0.47</u>	<u>7.09</u>	<u>3.48</u>	<u>-6.01</u>	<u>1.59</u>
<u>NOM</u>	<u>6</u>	<u>0.46</u>	<u>0.47</u>	<u>9.00</u>	<u>2.91</u>	<u>-8.23</u>	<u>-1.95</u>
<u>GWS</u>	<u>6</u>	<u>0.47</u>	<u>0.73</u>	<u>8.37</u>	<u>2.13</u>	<u>-7.34</u>	<u>0.16</u>
<u>HAN</u>	<u>4</u>	<u>0.51</u>	<u>0.79</u>	<u>8.43</u>	<u>2.48</u>	<u>-7.11</u>	<u>0.11</u>
<u>MSP</u>	<u>5</u>	<u>0.58</u>	<u>0.58</u>	<u>6.21</u>	<u>2.67</u>	<u>-5.44</u>	<u>1.18</u>
<u>PSW</u>	<u>5</u>	<u>0.62</u>	<u>0.87</u>	<u>8.67</u>	<u>2.50</u>	<u>-7.64</u>	<u>-1.21</u>
<u>WFP</u>	<u>B</u>	<u>0.64</u>	<u>0.90</u>	<u>7.90</u>	<u>4.27</u>	<u>-7.10</u>	<u>-3.55</u>
<u>DHS</u>	<u>6</u>	<u>0.64</u>	<u>0.87</u>	<u>8.19</u>	<u>2.49</u>	<u>-7.13</u>	<u>-0.96</u>
<u>KPW</u>	<u>5</u>	<u>0.65</u>	<u>0.65</u>	<u>8.33</u>	<u>2.83</u>	<u>-7.46</u>	<u>-1.01</u>
<u>WFH</u>	<u>5</u>	<u>0.65</u>	<u>0.65</u>	<u>7.30</u>	<u>2.44</u>	<u>-6.53</u>	<u>-0.46</u>
<u>FRP</u>	<u>5</u>	<u>0.66</u>	<u>0.92</u>	<u>7.08</u>	<u>2.74</u>	<u>-6.14</u>	<u>-0.80</u>
<u>HBF</u>	<u>2</u>	<u>0.71</u>	<u>0.93</u>	<u>7.94</u>	<u>3.32</u>	<u>-6.96</u>	<u>-1.98</u>
<u>SPS</u>	<u>10</u>	<u>0.71</u>	<u>0.72</u>	<u>7.10</u>	<u>2.93</u>	<u>-5.81</u>	<u>-0.57</u>
<u>PHX</u>	<u>5</u>	<u>0.71</u>	<u>0.95</u>	<u>8.27</u>	<u>4.45</u>	<u>-7.37</u>	<u>-3.66</u>

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