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Coupling physics-based mesoscale weather models and deep-learning microscale models for outdoor thermal comfort assessments.

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Urban populations are disproportionately affected by heat stress and heat-related health risks caused by climate change. To assess outdoor thermal comfort of humans using indices such as the Universal Thermal Climate Index (UTCI), air temperature, humidity, wind speed and the three-dimensional radiative environment (T_{mrt}) must be accurately represented. However, the influence of these variables on thermal comfort depends on the spatial and temporal scale and varies significantly within urban areas. While mesoscale variability dominates thermodynamic conditions, urban morphology and surface conditions control wind and radiant fluxes, as well as their temporal variance at local- and microscale.

The multiscale nature of the urban environment poses a significant challenge in modelling urban thermal comfort on a meaningful scale. Although physics-based numerical weather prediction (NWP) models with urban parameterisations can accurately depict urban–atmosphere interactions and local-scale processes across large model domains and over long time periods, they are limited to hectometer-scale resolutions and idealised urban geometries. Conversely, high-resolution urban climate models can resolve street-level microclimatic processes; however, they have limited spatial extent and temporal coverage due to computational constraints. While recent deep learning approaches have shown promising results in emulating microscale urban climate models, these approaches are typically applied offline and lack dynamic urban–atmosphere interactions. This restricts their ability to capture urban-induced feedback at meso- to local-scales.

In this study, we present a hybrid meso-to-microscale modelling chain that couples the physics-based ICON model, using the TERRA_URB urban parameterisation scheme, with a deep-learning-based microscale model that resolves buildings for the entire Greater Paris agglomeration. The ICON model was run at a spatial resolution of 1 km over a six-month period in summer 2023 to estimate local-scale air temperature and humidity while accounting for urban–atmosphere interactions such as downwind effects of the urban plume. We then trained, evaluated, and coupled a deep learning model to estimate T_{mrt} at the microscale (1 m) and coupled a diagnostic wind speed model to estimate wind speed at a resolution of 2 m. We subsequently computed the UTCI across the entire urban agglomeration of Greater Paris at a resolution of 1 m. The model

domain encompasses Greater Paris (35 km x 37 km). It was chosen as a test case due to its size, which introduces large-scale urban–atmosphere interactions and variability in urban morphology types. This enables the deep learning model to be trained holistically and improves the generalisation capability.

We demonstrate that coupling physically consistent mesoscale dynamics with data-driven microscale diagnostics leverages the strengths of numerical and deep learning-based models. The proposed model chain is scalable and computationally efficient. It presents a method for assessing human-scale thermal comfort across spatial and temporal scales, thereby supporting urban heat risk analysis and climate adaptation planning.