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Ultrafine-Resolution Urban Climate Modeling: Resolving Processes Across Scales

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Key Points:

- Ultrafine-resolution urban climate models, such as building-resolving large-eddy simulation (LES), enhance process representation and coupling with coarser models
- High computational costs, model uncertainties, and gaps in urban process representation limit the scalability of urban LES models
- Machine learning approaches offer a promising alternative to emulate complex processes and improve computing efficiency

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Abstract Recent advances in urban climate modeling resolution have improved the representation of complex urban environments, with large-eddy simulation (LES) as a key approach, capturing not only building effects but also urban vegetation and other critical urban processes. Coupling these ultrafine-resolution (hectometric and finer) approaches with larger-scale regional and global models provides a promising pathway for cross-scale urban climate simulations. However, several challenges remain, including the high computational cost that limits most urban LES applications to short-term, small-domain simulations, uncertainties in physical parameterizations, and gaps in representing additional urban processes. Addressing these limitations requires advances in computational techniques, numerical schemes, and the integration of diverse observational data. Machine learning presents new opportunities by emulating certain computationally expensive processes, enhancing data assimilation, and improving model accessibility for decision-making. Future ultrafine-resolution urban climate modeling should be more end-user oriented, ensuring that model advancements translate into effective strategies for heat mitigation, disaster risk reduction, and sustainable urban planning.

Plain Language Summary Cities have unique climates shaped by engineered structures, vegetation, and human activities. Numerical models are necessary to understand urban heat, air pollution, extreme weather, and the effectiveness of various mitigation and adaptation strategies for extreme events. But many global and regional models oversimplify how cities interact with the atmosphere. Recent advances in computing power and data sets have made it possible to develop more detailed urban climate models, including new approaches that better capture airflow, heat exchange, and other urban processes. However, these detailed models still face high computational costs, uncertainty in how physical processes are represented, and gaps in representing some urban features. New observational data sets and machine learning approaches provide promising solutions to address these gaps. Further improvements in ultrafine-resolution urban climate modeling will help cities better prepare for extreme weather conditions, improve air quality, and foster long-term sustainability and resilience.

1. Introduction

Cities are complex environments where interactions between the heterogeneous built system, natural systems, human activities, and the atmospheric boundary layer create unique meteorological and climatic conditions that differ from their surrounding areas (Oke et al., 2017). While some general circulation models and Earth system models have incorporated improved urban representations (Katzfey et al., 2020; D. Li et al., 2016; Oleson & Feddema, 2020), most global models and their downscaled regional ones still rely on (over)simplified urban representations that lack the granularity necessary to capture finer-scale heterogeneity in cities (Hertwig et al., 2021; L. Zhao et al., 2021). This limitation also extends to many operational numerical weather prediction models (e.g., Dowell et al., 2022). With growing urban populations and changing environmental conditions, very high-resolution urban climate simulations within regional and global models have become increasingly needed. Ultrafine-resolution urban climate simulations—here defined as those with horizontal grid spacings finer than a few hundred meters—covering a range of scales from non-building-resolving to building-resolving. They provide the granularity needed to resolve critical urban features such as building geometry, land cover variability, and anthropogenic emissions, along with their interactions with the atmosphere. This level of detail is not only important for advancing scientific understanding but also for informing decision-making in services.

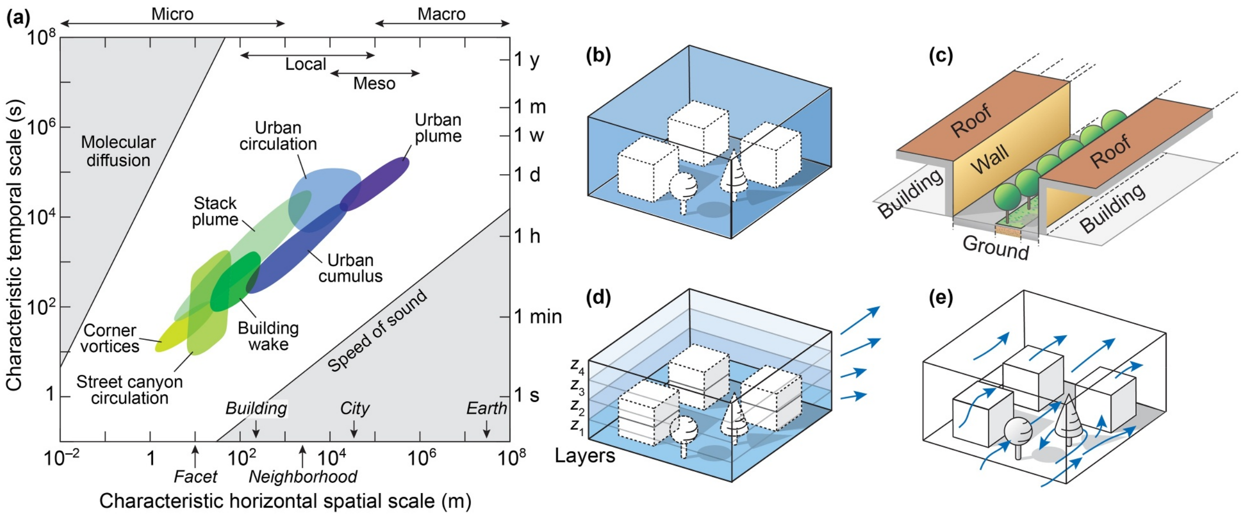

Figure 1. (a) Horizontal spatial and temporal scales of representative urban wind phenomena and (b)–(e) commonly used modeling approaches within the urban canopy layer: (b) the bulk approach, which neglects internal heterogeneity within the urban canopy layer; (c) the single-layer urban canopy model (UCM) that uses simplified street canyon geometry, with urban vegetation integrated; (d) the horizontal averaging approach, commonly used in multi-layer UCMs, which resolves vertical variations in atmospheric properties but neglect within-layer horizontal heterogeneity; and (e) the fully building-resolving approach, typically through computational fluid dynamics approaches such as large-eddy simulation. (a)–(b) and (d)–(e) are adapted from Oke et al. (2017), and (c) is adapted from C. Wang et al. (2021). Arrows in blue represent wind.

Driven by societal needs and technological progress, recent advances in urban climate modeling have improved the ability to capture urban heat stress, air pollution, and risks associated with extreme weather events (Lean et al., 2024; Y. Zhao et al., 2023). These advancements have been further accelerated by increasing computational power and the growing availability of urban data sets, enabling the development of physics-based, ultrafine-resolution urban climate models that range from advanced urban canopy parameterizations to computational fluid dynamics (CFD) approaches such as Reynolds-averaged Navier–Stokes (RANS) and large-eddy simulation (LES) (Carmeliet & Derome, 2024; Lean et al., 2024). These fine-scale models can resolve micro- to local/neighborhood-scale urban processes that are often highly parameterized in coarser global and regional models. However, achieving ultrafine-resolution urban climate simulations in regional and global models requires the numerical representation of processes across scales (Figure 1a) while balancing the increasing computational costs.

A recent step toward addressing this challenge is the development of City-LES, a multi-scale urban climate model that combines meteorological modeling and engineering CFD approaches (Kusaka et al., 2024). This model demonstrates the potential for detailed simulation of urban atmospheric dynamics, thermal environments, and heat stress indices. Building on this progress, the goal of this commentary is to provide a forward-looking perspective on the emerging capabilities of ultrafine-resolution urban climate simulations in climate and weather models, and to underscore the need for further advancements in model development and urban data sets to improve cross-scale representation. Strengthening these capabilities will allow urban climate simulations to better support sustainable and resilient urban development in a changing climate.

2. Progress Toward Ultrafine-Resolution Urban Climate Modeling

The increasing resolution of global and regional/mesoscale climate and weather models, from coarse grids of approximately one degree to eventually hectometers, has greatly improved the modeling of urban environments, necessitating better representation of urban heterogeneity. The traditional slab or bulk parameterizations (Figure 1b) simplify urban areas into homogeneous surfaces within numerical grids (e.g., Chen et al., 2004), which largely underrepresent the complex heat, moisture, and momentum exchanges within the urban canopy layer (Thompson et al., 2025). Recognizing these limitations, urban canopy models (UCMs) with varying complexity have been developed (Grimmond et al., 2010; Lipson et al., 2024). Single-layer UCMs (Figure 1c) approximate urban geometry with idealized street canyons without explicitly resolving vertical variations in atmospheric conditions below the mean building height (Kusaka et al., 2001; Masson, 2000). Multi-layer UCMs

(Figure 1d) improve upon this by simulating vertical profiles and horizontal advections when coupled with atmospheric models (Martilli et al., 2002). Recent advancements include parameterizing advection and vertical profiles within single-layer UCMs (Schoetter et al., 2020) and incorporating realistic urban vegetation and heat mitigation strategies (Krayenhoff et al., 2020; C. Wang et al., 2021; J. Yang et al., 2015). Similarly, urban air quality modeling has evolved toward street network models that account for localized emission sources and dispersion pathways (Kim et al., 2018; Soulhac et al., 2011).

However, UCMs, which are essentially land surface models, are not designed to solve flow equations on their own. When applied in climate and weather models operating at hectometric or finer resolutions, despite with an atmospheric model handling the dynamics, the simplified parameterizations within the UCM cannot resolve small-scale flow variations and turbulence within the canopy layer. This limitation persists even in relatively more complex UCMs that incorporate 3D urban geometry (Figure 1e; e.g., Krayenhoff & Voogt, 2007). At these resolutions, models operate well within the turbulence gray zone or terra incognita (Honnert et al., 2020; Wyngaard, 2004) and extend into the building gray zone (Barlow et al., 2017), where conventional turbulence parameterizations developed for coarse-scale models become unreliable. RANS-based models have been widely used in urban climate research to capture processes and conditions where turbulence is less dominant (e.g., Blocken, 2015; Liu et al., 2017; Y. Zhao et al., 2025). Nevertheless, at ultrafine resolutions, climate and weather models essentially operate in LES mode, which explicitly resolves larger turbulent eddies while parameterizing subgrid-scale motions. LES models provide a time-evolving representation of turbulence with improved spatial and temporal fidelity for urban atmospheric dynamics. Compared to Direct Numerical Simulation, which resolves all turbulent scales but is computationally infeasible for large urban domains, LES balances accuracy and computational efficiency, making it more suitable for coupled ultrafine-resolution urban climate simulations.

Traditional urban LES models have been developed as standalone tools to study micro- and neighborhood-scale canonical flow and turbulence problems. Initially, these models relied on simplified urban geometries, such as periodic street canyons and building arrays, but have since evolved into more realistic, building-resolving simulations, providing unprecedented resolution of urban flow dynamics (Bou-Zeid et al., 2009; Giometto et al., 2017; Kanda et al., 2004) (Figure 1e). However, they typically operate under quasi steady state assumptions with prescribed inflow conditions, rather than evolving with realistic atmospheric conditions, partly due to high computational costs (Cheng & Porté-Agel, 2015; Q. Li et al., 2016). Their focus on turbulence also means that other key urban processes such as radiation, heat storage, evapotranspiration, and moisture exchanges are often overlooked. Additionally, computational constraints limit their application to small-domain, short-term simulations. To address these limitations, several studies have attempted to couple LES with mesoscale models, most notably through the mesoscale Weather Research and Forecasting model. But many implementations still either relied on bulk urban representation (Y. Wang et al., 2023) or explicitly resolved buildings while neglecting other urban components (Chen et al., 2011; Muñoz-Esparza et al., 2025). A more comprehensive cross-scale approach requires integrating detailed urban morphology, including complex building layouts, vegetation, and anthropogenic heat sources, into LES models to enhance their capability for ultrafine resolution simulations.

Continued progress in LES modeling has further expanded its capabilities, allowing for a more complete representation of urban environments beyond just buildings. Recent efforts have incorporated vegetation, building heat exchanges, and complex radiation interactions among urban components (e.g., Resler et al., 2017; Suter et al., 2022). In addition, LES models have evolved in their representation of air pollution transport and chemical reactions to better capture urban air pollution heterogeneity (Maronga et al., 2020; Tseng et al., 2006; Vinuesa et al., 2006). Compared to earlier LES studies (e.g., Chen et al., 2011), models such as City-LES (Kusaka et al., 2024), PALM-4U (Maronga et al., 2020; Pfafferott et al., 2021), and uDALES (Owens et al., 2024; Suter et al., 2022) exemplify these advancements by integrating a broader range of urban features into ultrafine-resolution turbulence-resolving simulations (Figure 2). As these models continue to evolve, they are increasingly being explored for coupling with larger-scale models, progressively bridging micro- and neighborhood-scale processes with large-scale atmospheric dynamics to enable comprehensive urban environmental assessments.

Despite these advances, applying building-resolving LES across large urban domains within weather and climate models remains computationally challenging. For hectometric resolution simulations, an alternative is the hybrid LES–UCM approach, which couples coarse-resolution, non-building-resolving LES with advanced UCMs (e.g., Karttunen et al., 2024). This method allows LES to resolve turbulence and flow dynamics, while UCMs represent

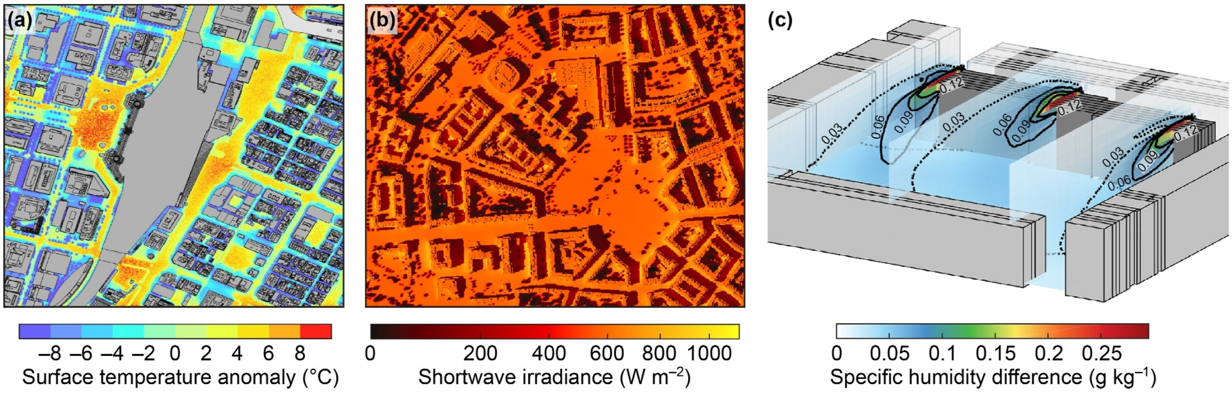

Figure 2. Examples of ultrafine-resolution urban climate modeling using LES: (a) surface temperature anomalies relative to an average surface temperature of 42.0°C around Tokyo Station, Japan on 19 August 2013, simulated with the City-LES model, adapted from Kusaka et al. (2024); (b) instantaneous total shortwave irradiance on horizontal surfaces in Prague, Czech Republic on 7 August 2015, simulated with PALM-4U, adapted from Maronga et al. (2020); (c) humidifying effect of a green roof, expressed as the increase in specific humidity in London, UK on 21 Jun 2017, simulated using uDALES, adapted from Suter et al. (2022).

urban radiation and heat exchanges with improved computational efficiency. By combining the strengths of both models, this approach offers a potentially scalable pathway toward ultrafine-resolution urban climate modeling within regional and global models when computational resources are relatively limited.

3. Challenges and Opportunities

While LES has emerged as a powerful tool for ultrafine-resolution, turbulence-resolving urban climate modeling, several challenges limit its broader application. One major limitation is its sensitivity to atmospheric boundary layer stability, particularly under extremely stable conditions, where meeting the LES criterion of resolving ∼80% of the turbulent kinetic energy may require extremely fine grid resolutions (e.g., Resler et al., 2024). Specifically, conventional subgrid-scale models are often developed for specific resolution ranges and may not properly capture turbulence across different stability regimes (Honnert et al., 2020). In addition, bulk cloud microphysics schemes, designed for coarse-resolution models, are inadequate for LES and require adaptable approaches across spatial and temporal resolutions (Lean et al., 2024). Another key challenge is the high computational cost of LES, especially for long-term, large-domain simulations. This is partly why most large-domain urban climate simulations have mainly used RANS models (Blocken, 2015; Toparlar et al., 2017), while LES applications to date remain short-term, limited-area demonstrations (e.g., Kusaka et al., 2024). The computational cost also makes urban LES less feasible for long-term historical analyses and real-time forecasting. Addressing these challenges requires improved computational techniques and numerical schemes that effectively bridge scales (Shin et al., 2021; Wiersema et al., 2020). An example of emerging solutions is the use of GPU-based LES frameworks, such as FastEddy developed by the National Center for Atmospheric Research (Sauer & Muñoz-Esparza, 2020). These improvements are particularly critical for urban applications including hazardous material dispersion, emergency response, and public health interventions, where fast and reliable forecasts at fine scales are essential (Creutzig et al., 2019; Pontiggia et al., 2010).

Despite progress in ultrafine-resolution modeling, several urban processes remain inadequately represented, which can limit the reliability and applicability of simulations for specific scientific and decision-making needs (Table 1). Anthropogenic heat emissions are often treated as static or prescribed sources rather than dynamic fluxes influenced by building operations,

occupant behavior, and transportation systems (Chen et al., 2011). Compared to simplified building energy models used in global and mesoscale models (X. Li et al., 2024), improved building energy modeling reflecting heterogeneous building stock characteristics (C. Wang et al., 2023) is necessary. Similarly, the simplified street canyon geometry in UCMs may introduce biases in radiation exchange estimates for typical urban neighborhoods (Schoetter et al., 2023). The explicit representation of urban vegetation, especially trees, beyond the simplified "big leaf" approach is needed (Bonan et al., 2021). Although earlier modeling efforts have attempted to resolve urban hydrological processes, such as runoff and groundwater interactions (Omidvar et al., 2019; Talebpour et al., 2021), these processes still remain poorly represented in most urban climate models (Jongen et al., 2024).

Table 1
Examples of Improvements for Urban Process Modeling and Their Relevance for Research and Decision-Making

Model improvements	Description	Example questions and applications
Dynamic anthropogenic heat modeling	Move beyond surface-level, static or prescribed fluxes by incorporating building operations, occupant behavior, transportation, and industrial activities	Evaluation of urban heat stress and heat mitigation strategies; coupled heat emissions with co-emitted air pollutants
Heterogeneous building energy modeling	Represent diverse building types, vintage, materials, envelope, equipment, and occupant behavior	Urban energy forecasts; evaluation of building retrofits and efficiency improvement
Dynamic pollutant emission modeling	Move beyond static emission inventories to account for temporal and spatial variability in air pollutant emissions	Urban air quality forecasts; air pollution exposure assessments
Improved urban geometry representation	Incorporate corrections or adjustments into simplified urban geometry for better radiation estimates	Pedestrian thermal comfort evaluation; pollutant exposure assessments
Improved urban vegetation representation	Resolve tree canopy structure beyond the big-leaf approach	Evaluation of heat mitigation with nature-based solutions; biogenic carbon exchange estimates
Urban hydrological processes	Simulate runoff generation, infiltration, and groundwater interactions	Flood risk evaluation; design of green infrastructure; air pollutant deposition
Underground infrastructure	Represent subsurface heat and moisture exchanges involving foundations, tunnels, and transit systems	Subsurface heat storage analysis; subsurface ventilation
Novel mitigation strategies	Represent novel heat mitigation measures, renewable energy systems, and adaptive technologies	Local-scale intervention assessments; evaluation of side-effects on pollutant dispersion

The role of underground infrastructure in urban heat exchange and water exchange is another key aspect that requires better representation. Furthermore, incorporating novel urban mitigation strategies, such as mist cooling systems (Kusaka et al., 2024) and renewable energy integration (Zonato et al., 2021), can improve the applicability of ultrafine-resolution urban climate modeling for sustainable urban planning and climate adaptation.

An important strategic consideration in ultrafine-resolution urban climate modeling within regional and global models is whether to pursue fully building-resolving approaches, which offer greater detail but are computationally more expensive, or to further improve non-building-resolving parameterizations in more efficient hybrid approaches (e.g., LES coupled with UCM). The choice between these approaches should be guided by specific modeling objectives, spatial and temporal scales of interest, and available computational resources, balancing the need for process representation with practical feasibility. For example, if the goal is to quantify citywide average urban heat island intensity, resolving detailed airflow within street canyons may not be necessary. In comparison, applications such as pedestrian-level heat and pollution exposure and localized pollutant dispersion certainly require finer-scale urban flow and turbulence representation. Variable-resolution regional and global simulations provide another scalable solution for cross-scale urban climate modeling by refining grid resolution in targeted urban areas while maintaining coarser resolutions elsewhere (Huang et al., 2016; McGregor, 2015). However, model coupling across scales introduces complexities such as potential double-counting in urban land surface processes, particularly aerodynamic effects of buildings (Sützl, Rooney, Finnenkoetter, et al., 2021) and the subgrid representation of urban vegetation in the tiling/mosaic approach. It is noteworthy that idealized LES studies will remain valuable as testbeds for hypothesis testing, process understanding, model validation under controlled conditions, and the development of urban parameterization schemes (Nagel et al., 2023; Nazarian et al., 2020; Sützl, Rooney, & van Reeuwijk, 2021).

Advancing ultrafine-resolution urban climate modeling heavily relies on the availability of high-quality data sets for model initialization, boundary conditions, validation, and evaluation (Masson et al., 2020; Radović et al., 2024). Essential model inputs include long-term, high-resolution land cover data, detailed building geometry and material properties, and spatially and temporally resolved anthropogenic heat, moisture, and pollutant emissions. Some recent high-resolution examples include a GEDI-based 150-m global building height data set (Ma et al., 2024), a Sentinel-based 100-m global building morphology data set (R. Li et al., 2024), and a global three-dimensional building footprint data set (Che et al., 2024). Urban soil texture data, often disturbed by human activities yet critical for surface energy and moisture fluxes (J.-L. Yang & Zhang, 2015), are another missing piece for better capturing heterogeneity in urban hydrology and land–atmosphere interactions. Reliable observational data are equally important for model evaluation and improvement, necessitating coordinated efforts between modeling and observational campaigns, such as the U.S. Department of Energy's Urban Integrated Field Laboratories (https://ess.science.energy.gov/urban-ifls/) and the urbisphere project in Europe (Fenner et al., 2024). Additionally, novel data sources, such as crowdsourced and mobile measurements (Meier et al., 2017; Romero Rodríguez et al., 2020), present promising opportunities to complement weather station observations and improve spatial and temporal coverage.

With advancements in remote sensing and numerical simulations, very high-resolution urban data have become increasingly available, positioning machine learning (ML) and other data-driven approaches as valuable tools in ultrafine-resolution urban climate modeling. ML offers computationally efficient alternatives to traditional physics-based models, enabling city- or site-specific solutions, especially where detailed input data are lacking (P. Li & Sharma, 2024; Meyer et al., 2022; L. Zhao et al., 2021). ML can be integrated into physics-based urban climate models as differentiable components within numerical solvers to emulate certain computationally expensive processes, such as cloud microphysics, radiation, and even flow fields (Hora & Giometto, 2024; Kashinath et al., 2021; Lu et al., 2023). Additionally, ML can enhance model–data integration, particularly in data assimilation (Geer, 2021), to improve observational constraints on urban climate modeling. ML (e.g., Large Language Models) can also help bridge gaps between simulations and end-users by translating and communicating complex model outputs in a clearer, more accessible way for stakeholders and the public (H. Li et al., 2025).

However, the physical interpretability and generalizability of ML-based models across diverse urban environments are still challenges to be addressed. ML-based models are often limited to short-term forecasts and are constrained by the quality, representativeness, and coverage of their training data. For example, an ML model trained on areas with regular urban geometry and conventional heat mitigation strategies is unlikely to achieve similar accuracy when applied to environments with complex urban forms or novel mitigation approaches not represented in its training data. Moreover, core processes governed by fundamental laws such as energy and momentum conservation should remain physics-based to ensure consistency. Consequently, physics-based models remain essential for urban climate modeling, not only in generating training data for ML algorithms, but also in providing interpretable, process-based understanding of urban climate dynamics. The synergy between ML and physics-based approaches represents a promising path forward for advancing ultrafine-resolution urban climate modeling while enhancing its practical applications.

4. Conclusions

Future urban climate modeling should strive to integrate multi-scale approaches with comprehensive process representations, diverse observational data sources, and data-driven techniques such as ML to improve efficiency and adaptability across different urban contexts. The effectiveness of ultrafine-resolution urban climate modeling depends on its practical applicability for stakeholders, policymakers, and urban planners in areas such as heat mitigation, disaster risk reduction, and emergency management. While improving the representation of urban physical processes remains important, future model development must also be end-user oriented to ensure interpretable, practical, and actionable results. Meanwhile, strengthening collaboration between researchers and end-users, especially practitioners, will be key to transforming models into effective tools for building resilient and sustainable cities.

Data Availability Statement

Data were not used, nor created for this research.

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