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OPINION

Uncertainty in urban climate modeling: Bridging the gap between science and policy

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Introduction

Urban climate simulations offer a means to observe, predict, and understand better the subtle changes in temperature, airflow, pollutant dispersion, and thermal comfort throughout a city. These models rely mostly on approaches like Reynolds-averaged Navier-Stokes (RANS) or Large Eddy Simulation (LES), and are implemented in software such as PALM [1], Solweig [2], ENVI-met [3], and FITNAH-3D [4], among others. Often shown as colorful maps or moving 3D models, the results of the models could give the impression that we can fully control the complex and unpredictable nature of our cities. Yet behind this apparent precision lies a more fragile and uncertain foundation.

Each model rests on many assumptions, patchy data, and necessary simplifications, most of which stay out of sight [5]. The actual thermal properties of urban materials, heat generated by inhabitants, and even the precise geometry of buildings and green spaces are rarely known with certainty. Modelers often use default values, averages, or estimates to address these gaps without fully appreciating the extent to which these choices influence the outcomes. Understanding how these different factors interact with one another is far from straightforward, adding yet another layer of uncertainty to the predictions. City planners and decision-makers, relying heavily on these simulations [6] risk making significant choices without a clear understanding of the reliability or limitations of the scenarios: the uncertainty is often ignored or barely mentioned, creating an illusion of control and confidence. This short opinion review aims to highlight the key sources of uncertainty in urban climate modeling and to critically examine the prevailing practices that tend to neglect or downplay their significance.

Source of uncertainty

Essential Climate Variables (ECVs, [7]) are key physical, chemical, or biological variables that are critical for understanding and modeling the climate system. Within the urban context, typical ECVs include air temperature, humidity, wind speed, radiation fluxes, and surface properties. In urban climate modeling, uncertainty in ECVs reflects the range of errors arising from interactions between complex urban surfaces (e.g., buildings, roads, vegetation) and atmospheric processes, as well as from limitations in observation and modeling methods.

Within the context of urban climate modeling, uncertainties in ECVs can be broadly grouped into two main categories:

- *Model-inherent limitations*: Any simulation is a simplified abstraction of reality and often models idealized conditions, such as a hot, clear day with no wind. Software like FITNAH-3D and ENVI-met uses RANS approaches that simplify turbulence rather than fully resolving its complexity. In contrast, LES methods capture more detail but require much more computing power, making them less practical for large-scale or long-term urban climate simulations. Additional ambiguity arises from the modeling of physical processes. The fundamental laws of heat transfer, radiation, and fluid dynamics are well known, but their application in dense, heterogeneous urban settings is complex [8].
- *Input-related uncertainties*: The data needed to feed the models often comes with its flaws: processing errors, outdated datasets, inconsistent resolutions, and overly generalized depictions of urban form. These external factors, though sometimes subtle, can significantly shape the outputs of even the most advanced simulations. Buildings differ not only in height and shape but also in materials, color, and condition, all of which affect heat exchange. Vegetation varies by species, density, and season. Because collecting such detailed data citywide is costly or impractical, modelers rely on proxies or averages that smooth out key differences in structure and surface. This spatial homogenization masks the heterogeneity driving local airflow and thermal dynamics, leading to oversimplified results and underestimated uncertainty [9].

Implication for urban planning and policy

Urban planners, architects, and policymakers increasingly rely on climate simulations to justify designs, zoning laws, and adaptation strategies. Hidden assumptions and uncertainties in models can lead to misguided or even detrimental decisions based on their outputs. For example, a plan to increase urban greenery based on a simulation that underestimates local airflow might fail to deliver the expected cooling benefits [10]. Similarly, heat mitigation strategies derived from incomplete data on building materials could lead to investments with limited returns or unintended side effects [11]. Additionally, relying on data with coarse spatial resolution can mask critical microclimatic variations, further reducing the effectiveness of urban planning decisions [12].

Capturing microclimates (e.g., street-canyon effects) requires fine-resolution grids, but computational costs limit large-scale or long-term simulations. Mesoscale models (1 km resolution) improve accuracy but still approximate urban features like building morphology. Downscaling adds uncertainty, and simplifications distort airflow and temperature predictions. The trade-off between detail and feasibility propagates uncertainty into planning decisions.

To address computational constraints, GEO-NET GmbH developed the QGIS plugin Klimascanner, enabling rapid comparison of planning scenarios' impacts on temperature, wind, and urban comfort (Fig 1). While its AI-driven statistical models enhance projection credibility, they remain constrained by underlying physical models like FITNAH-3D and region-specific training data, limiting validity to documented European climates. This dataset dependence introduces uncertainty beyond the training domain, necessitating transparent communication of limitations to prevent misplaced confidence in results.

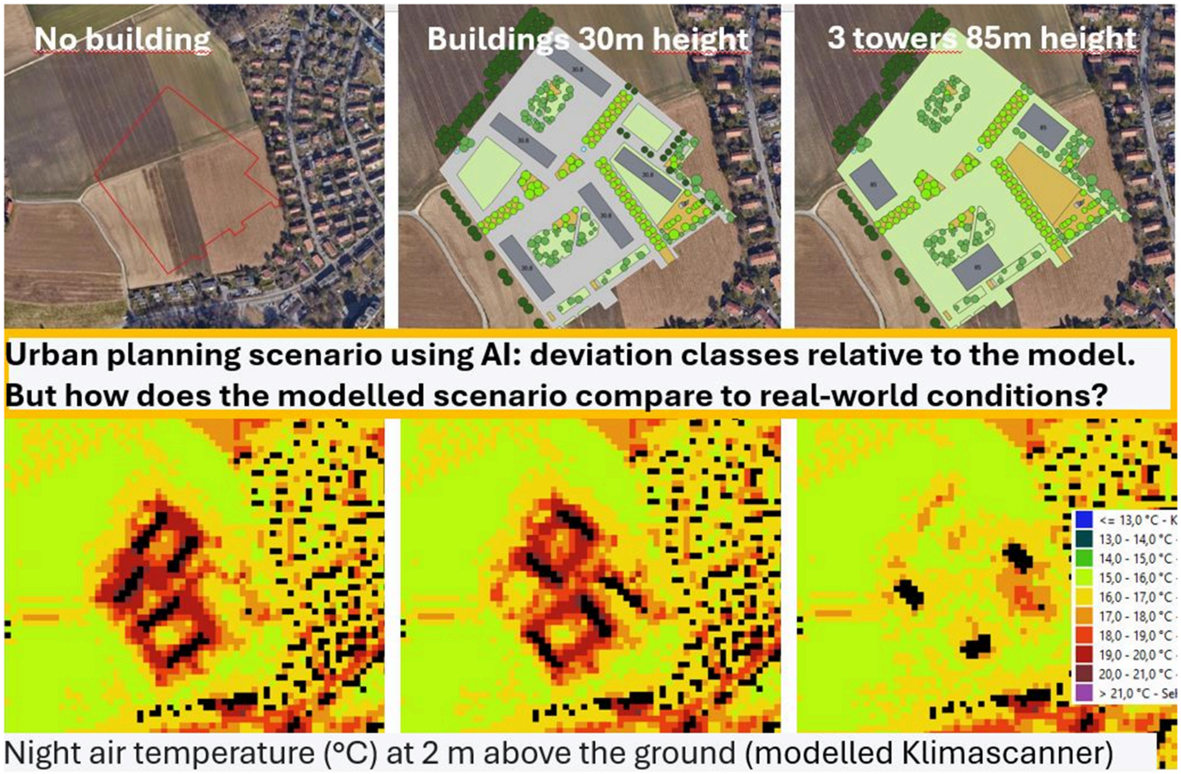

Fig 1. Comparison of two urban planning scenarios showing modeled nighttime air temperature at 2 m above ground. The temperature fields were generated using KlimaScanner.

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Why is uncertainty rarely addressed, and why validation with real data is only a partial answer

The near-total absence of uncertainty in published modeling studies is not accidental. It reflects structural, cultural, and sometimes strategic choices. We cite for instance

- **Computational constraints**: Uncertainty quantification methods (e.g., Monte Carlo, sensitivity analyses) are impractical for LES models due to extreme computational demands. Repeating simulations hundreds of times exceeds available resources, limiting their use in operational modeling.
- **Tool limitations**: Most climate modeling platforms lack built-in uncertainty analysis. Ensemble methods reveal scenario variability but ignore structural biases, while surrogate models (e.g., Gaussian processes) reduce computational costs but add abstraction layers. No standardized framework exists for transparent uncertainty integration.
- **Data scarcity**: Input data often lacks reliable distributions or confidence intervals. While high-resolution remote sensing and IoT networks improve data availability, biases persist due to sampling limitations. [13] highlights four dataset ensemble types to address these issues, but gaps remain.
- **Big Data and AI**: AI-driven preprocessing enhances handling of heterogeneous urban data but introduces systematic biases and obscures uncertainty sources. These biases can propagate through simulations, particularly in UHI forecasting, where reliable uncertainty quantification is critical [14].

- **Cultural inertia**: Scientific publishing and policy contexts favor clear, decisive results over nuanced uncertainty discussions. Including uncertainty may reduce the persuasiveness of model outputs in planning and decision-making [15].

Validating urban climate models against real-world observations is essential but inherently complex [16]. A key challenge lies in the spatial mismatch between modeled outputs, typically averaged over grid cells, and observational data collected at discrete sensor points. Long-term datasets for assessing seasonal or climatic trends are often sparse, fragmented, or inconsistent, undermining robust validation [13]. Uncertainty is further compounded by interdependencies between ECVs such as temperature, humidity, wind, and anthropogenic activity, which complicate model evaluation.

While correlation metrics (e.g., R^2) are frequently cited as evidence of model reliability, high values do not guarantee accuracy. A model systematically overestimating temperatures by 2°C could still yield an R^2 of 0.95 if trends align, creating a misleading impression of precision. Scenario rankings based on minor modeled differences may prove unreliable once uncertainty is accounted for, potentially reversing apparent "optimal" solutions. Biases introduced by improper Big Data normalization or AI preprocessing can compromise decision robustness [14].

In short, uncertainty is inconvenient. This complicates interpretation, hinders clear communication of findings, and raises questions about reliability.

Conclusion

Uncertainty is often ignored due to practical constraints (computation, data, software) and cultural preferences for clear, actionable results over nuanced analyses. Yet transparency is critical: urban climate models must disclose uncertainties to remain credible. We call for standardized uncertainty reporting in research and practice. While AI tools show promise, their limitations must be acknowledged to preserve public trust. Models should present plausible futures—not predictions—dependent on evolving assumptions. Achieving this requires collaboration across sectors and robust data governance to ensure reliability in decision-making.

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