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Digitizing cities for urban weather: representing realistic cities for weather and climate simulations using computer graphics and artificial intelligence

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Abstract

Due to their importance in weather and climate assessments, there is significant interest to represent cities in numerical prediction models. However, getting high resolution multi-faceted data about a city has been a challenge. Further, even when the data were available the integration into a model is even more of a challenge due to the parametric needs, and the data volumes. Further, even if this is achieved, the cities themselves continually evolve rendering the data obsolete, thus necessitating a fast and repeatable data capture mechanism. We have shown that by using AI/graphics community advances we can create a seamless opportunity for high resolution models. Instead of assuming every physical and behavioral detail is sensed, a generative and procedural approach seeks to computationally infer a fully detailed 3D fit-for-purpose model of an urban space. We present a perspective building on recent success results of this generative approach applied to urban design and planning at different scales, for different components of the urban landscape, and related applications. The opportunities now possible with such a generative model for urban modeling open a wide range of opportunities as this becomes mainstream.

Keywords Urban computational science, Urban modeling, Artificial intelligence, Generative AI

Extreme weather and climate impacts are on the rise and often disproportionately affect cities more than rural areas. The C-40 group has outlined that cities lose about $200 billion annually from climate stressors. Climate impacts for the cities can be from 1.4% to 10.9% of its GDP by 2100 (Estrada et al., 2017). Further, rising global temperatures and climatic extremes have a disproportionately stronger effect on cities due to the urban infrastructure and the 'urban heat island' effect. Thus, the combination of changing climate and growing cities will likely foment heat spells and extreme weather events with urban areas being at the epicenter. Consequently, there is significant interest to represent cities in advanced environmental simulation models and to successfully simulate the urban-environment interaction in order to design new cities, evolve current cities, and provide what-if tools for a more sustainable urban infrastructure.

Representing cities within a region, nation, or globe in extreme weather and climate models is therefore an emergent computational challenge. Historically, cities have been treated as a sub-grid scale process because of their small geographical footprint. Recently, different large-scale community-based (Ching et al., 2018) and sensor-based efforts are underway to improve urban representation and the physics-based models (Chen et al.,

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2011), along with sophisticated large-scale field experiments and programs. One recent example is the $100 M initiative through the US Department of Energy to form collaborations called Urban Integrated Field Labs that will focus on improving our understanding of urban systems (Cho, 2021).

The computational modeling of large-scale urban-environment interaction via the use of weather and climate simulation models necessitates providing a variety of detailed information about the urban space, including the aspect ratio of street canyons and/or building spacing, building surface fraction, and impervious and pervious surface fractions. Such urban morphological features are translated into the model's representation of aerodynamic roughness that affects winds, surface emissivity and surface albedo that determines the radiative balance and thermodynamic environmental, vegetation, and anthropogenic heat sources. These morphological factors of the urban form, therefore also have direct linkage to environmental functions such as surface energy balance, radiative processes, boundary layer development, and dynamics which alters storms characteristics, cloud formation, and temperature and wind evolution.

Satellite-based measurements (e.g., LandSat, WorldView, or Planet Labs) provide some land-cover information and other orbiting LIDAR products yield some potential of height information at scale (e.g., ICESat, GEDI). City-sponsored and crowd-sourced efforts, such as OpenStreetMap, provide some cadastral data. However, aside from a few well-studied megacities (e.g., New York, Paris, Beijing, Tokyo) by far current data and sensors yield relatively incomplete descriptions of most cities. As such, they are difficult to integrate within simulation models, have limited resolutions, and hinder crucial what-if scenario creation.

One key observation is that computer graphics and artificial-intelligence (AI) based visual computing have been extremely successful in generating 2D images and 3D geometric models, including very detailed and plausible urban environments (e.g., Nishida et al., 2018, Zhang et al., 2021, He et al., 2023b, ESRI's CityEngine software). Thus, the capability to model urban environments with both highly meticulous form and function is clearly possible.

Therefore, instead of relying on an edge computing/sensor-based observation of all aspects of urban environments, we look to advances in graphics and AI to enable digital city generation producing realistic detailed urban form and function (Fig. 1). In particular, the combination of urban procedural modeling, stemming from computer graphics (and computer vision), with urban environmental modeling, all within a procedural generation framework, provides an efficient fit-for-purpose scalable approach. Instead of assuming every physical and

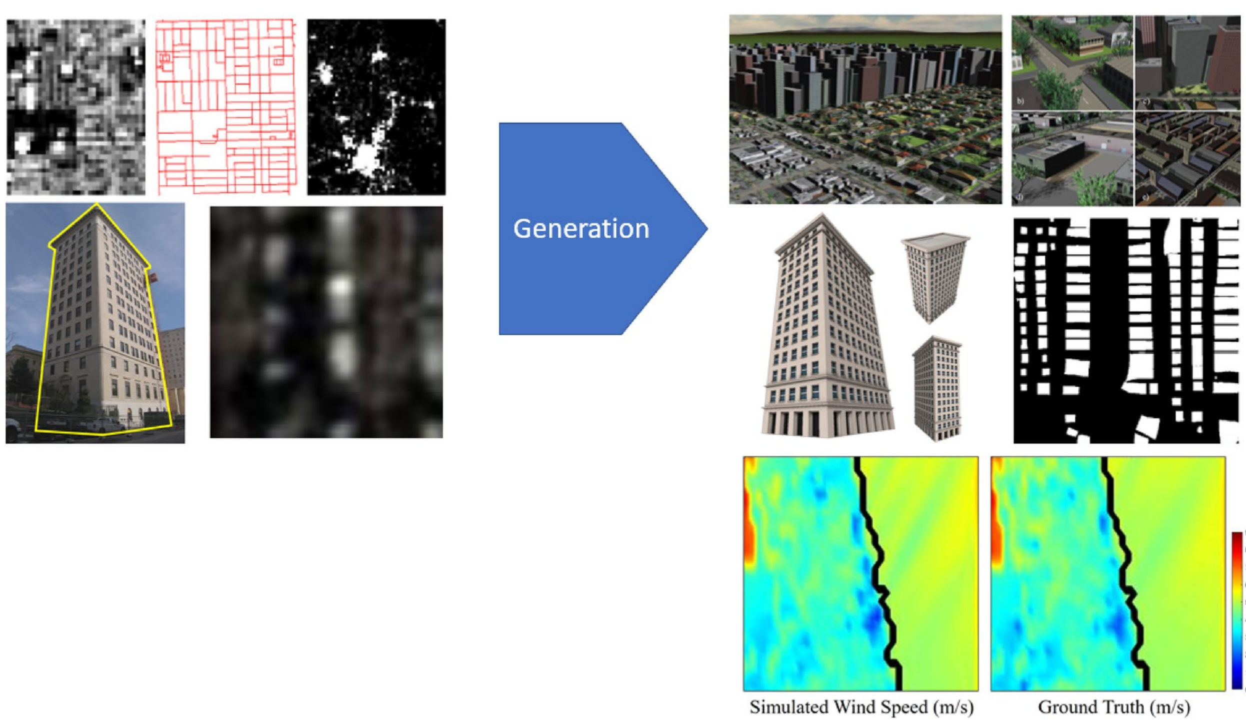

Fig. 1 Digitizing cities for urban weather. (left) Given only partial incomplete urban data, deep generative modeling enables generation (right) of complete building, neighborhood, and city models for urban extreme weather and climate predection planning, and mitigation

behavioral detail is sensed, a generative approach seeks to infer a fully detailed 3D fit-for-purpose model of an urban space effectively inferring the unseen.

We are already observing early demonstrations of this alternative generative approach applied to computational urban design and planning at different scales, for different components of the urban landscape, and for several applications. For example, at building scale generative modeling has been combined with deep learning to automatically create complete parameterized buildings from only a single ground/aerial photograph (Nishida et al., 2018). Despite not capturing all sides of the buildings, the resulting building envelopes have > 90% accuracy of building mass and facades. In other work, a generative approach exploited the relatively constrained space of roof shapes in order to automatically produce complete roofs from a single satellite image, yielding > 90% in roof shapes. Further, generative models have combined satellite imagery with spatial information on population, vegetation, and elevation (He et al., 2023a) to automatically create high-resolution synthetic building footprints, despite occlusions, noise, and limited resolution. Such a generative approach from heterogeneous data outperforms leading segmentation and super-resolution works by 43% on average for test cities worldwide (e.g., Chicago, Austin, Kitsap, Vienna, Tyrol) or large regions (e.g., 5000 square kilometers in Belgium).

At the neighborhood scale, generative methods have also had significant initial success. For example, a graph neural network is able to reproduce the neighborhood layouts in at least 28 well populated cities across North America, yielding over two million building footprints. A user study indicates this approach is preferred by at least 86.7% over prior approaches and performing better in 5 of the 6 typically used metrics (He et al., 2023b).

At city-scale, Zhang et al. (2021) has developed a fully automatic methodology for producing a 3D approximation of an urban area given satellite imagery, road networks, spatial population, and satellite-based elevation data. Hence, by analyzing heterogeneous data a synthetic approximation of a city can be generated at scale (e.g., Dublin, Hong Kong, Jacksonville, New Orleans, Paris, San Francisco, Chicago, and Toulouse producing per city almost 100,000 buildings, spanning 150 km^2, and with less than 1% error in parcel and building areas in the best case, and 5.8% error on average). A generative approach can also exploit spatio-temporal data and infer urban management rules to generate individual tree locations and counts despite individual trees not necessarily being visible from satellite due to occlusion and resolution limitations (Firoze et al., 2022). Analysis with four diverse cities (e.g., Austin, Indianapolis, Chicago, and Lagos, Nigeria), containing up to 225 km^2 and 144,788 trees per city region, yields accuracies of 87–97%. In a similar fashion, trees can be localized and segmented in dense forests surrounding urban locations (Firoze et al., 2023).

Generating complete and parameterized urban models has proven to better environmental modeling and planning applications. In particular, initial efforts were based on a mixture of crowd-sourced efforts and deep local climate zone (LCZ) generation methods (Zhu et al., 2022). For example, such LCZ generation was used to study the effect of green roofs over the Mumbai, India area and to improve heatwave prediction (for the June 8–25, 2017 European heatwave event) which is critical since urban dwellers are highly susceptible to heat waves with a fatality risk increasing by 4.5% for every 1 °C increase in heat wave intensity (Patel et al., 2022). Extreme rainfall forecasting and preemptive planning was improved by LCZ generation over Chinese megacities as well (Hu et al., 2023). An alternative generation approach is computing LCZ information automatically from geographical and socio-economical databases as has been done in France (Masson et al. 2020) and other European cities.

The further incorporation of detailed automatic urban generation at building, neighborhood and/or city scale has already been shown to be beneficial to local weather forecasting. Using a popular model (Chen et al., 2011), in comparison to a control run (using a national dataset of 44 city-scale LIDAR datasets captured by a large national project, NUDAPT) and to a run based on the crowd-sourced effort of the World Urban Database and Access Portal Tools (WUDAPT) initiative (Ching et al., 2018), the generative model approach equals or outperforms the crowd-sourced effort and almost matches the LIDAR-based model but of course without requiring a city-scale LIDAR capture! (Patel et al., 2023). Generative modeling has also shown to benefit flooding mitigation. Recently, there is a shift in focus from hard flood controls to increasing resilience by bettering the urban design process. In Mustafa et al. (2018), city models (Liege, Frankfurt, Paris, Brussels, Embourg, New York City) were used to study the influence of urban geometry (e.g., road width, orientation, curvature, etc.) on flow properties during flooding. The parameterized and generated urban model enabled studying what urban design rules produce a passive barrier against natural floods.

Going forward, these powerful computational generation methods can be fed into the growing Digital Twin efforts. For example, Destination Earth (DestinE) is a flagship initiative of the European Commission to develop a digital model of Earth at global scale (Bauer et al. 2021). This model can help monitor and predict natural phenomena as well as the urban-environment interface. NVIDIA has also announced the desire to create an Earth-scale realistic environment, making use of their

Omniverse platform. The described urban generative methods will also play a crucial role in developing these Earth-scale simulation and metaverse environments.

While measurements, and data processing of satellite products is critical to advance the field, complementary efforts such a from video gaming, regenerative tools and AI/ML based urban imagery can also directly benefit computational science modeling for real life urban decisions – and not just in a metaworld.

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Availability of data and materials
All referred to papers and results are available on contact author's website (www.cs.purdue.edu/homes/aliaga).

Declarations

Competing interests
Dr. Dev Niyogi is an editorial board member for the Computational Urban Science and was not involved in the editorial review, or the decision to publish, this article. All authors declare that there are no competing interests.

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