MetaCity: Data-driven sustainable development of complex cities

Yunke Zhang,[1,14] Yuming Lin,[1,14] Guanjie Zheng,[2,14] Yu Liu,[1] Nicholas Sukiennik,[1] Fengli Xu,[1] Yongjun Xu,[3,4] Feng Lu,[3,5] Qi Wang,[6] Yuan Lai,[7] Li Tian,[7] Nan Li,[8] Dongping Fang,[8] Fei Wang,[3,4,*] Tao Zhou,[9,*] Yong Li,[1,*] Yu Zheng,[10] Zhiqiang Wu,[11] and Huadong Guo[12,13]

*Correspondence: wangfei@ict.ac.cn (F.W.); zhutou@ustc.edu (T.Z.); liyong07@tsinghua.edu.cn (Y.L.)

Received: July 15, 2024; Accepted: December 23, 2024; Published Online: January 16, 2025; https://doi.org/10.1016/j.xinn.2024.100775

GRAPHICAL ABSTRACT

PUBLIC SUMMARY

- Rapid urbanization poses challenges for sustainable development in complex cities.
- MetaCity leverages the extensive potential of data-driven methods to tackle challenges of urban complexity.
- MetaCity integrates the discovery of urban problems, simulation of urban operations, and decision-making processes to optimize urban resource allocation.
- MetaCity presents significant implications across various applications for achieving Sustainable Development Goals.

MetaCity: Data-driven sustainable development of complex cities

Yunke Zhang,[1,14] Yuming Lin,[1,14] Guanjie Zheng,[2,14] Yu Liu,[1] Nicholas Sukiennik,[1] Fengli Xu,[1] Yongjun Xu,[3,4] Feng Lu,[3,5] Qi Wang,[6] Yuan Lai,[7] Li Tian,[7] Nan Li,[8] Dongping Fang,[8] Fei Wang,[3,4,*] Tao Zhou,[9,*] Yong Li,[1,*] Yu Zheng,[10] Zhiqiang Wu,[11] and Huadong Guo[12,13]

[1]Department of Electronic Engineering, Beijing National Research Center for Information Science and Technology (BNRist), Tsinghua University, Beijing 100084, China
[2]John Hopcroft Center for Computer Science, Shanghai Jiao Tong University, Shanghai 200240, China
[3]University of Chinese Academy of Sciences, Beijing 100049, China
[4]Institute of Computing Technology, Chinese Academy of Sciences, Beijing 100190, China
[5]Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[6]Department of Civil and Environmental Engineering, Northeastern University, Boston, MA 02115, USA
[7]School of Architecture, Tsinghua University, Beijing 100084, China
[8]School of Civil Engineering, Tsinghua University, Beijing 100084, China
[9]Big Data Research Center, University of Electronic Science and Technology of China, Chengdu 611731, China
[10]JD iCity, JD Technology & JD Intelligent Cities Research, Beijing 100176, China
[11]College of Architecture and Urban Planning, Tongji University, Shanghai 200292, China
[12]International Research Center of Big Data for Sustainable Development Goals, Beijing 100094, China
[13]Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China
[14]These authors contributed equally
*Correspondence: wangfei@ict.ac.cn (F.W.); zhutou@ustc.edu (T.Z.); liyong07@tsinghua.edu.cn (Y.L.)

Received: July 15, 2024; Accepted: December 23, 2024; Published Online: January 16, 2025; https://doi.org/10.1016/j.xinn.2024.100775

Citation: Zhang Y., Lin Y., Zheng G., et al., (2025). MetaCity: Data-driven sustainable development of complex cities. The Innovation **6(2)**, 100775.

Cities are complex systems that develop under complicated interactions among their human and environmental components. Urbanization generates substantial outcomes and opportunities while raising challenges including congestion, air pollution, inequality, etc., calling for efficient and reasonable solutions to sustainable developments. Fortunately, booming technologies generate large-scale data of complex cities, providing a chance to propose data-driven solutions for sustainable urban developments. This paper provides a comprehensive overview of data-driven urban sustainability practice. In this review article, we conceptualize MetaCity, a general framework for optimizing resource usage and allocation problems in complex cities with data-driven approaches. Under this framework, we decompose specific urban sustainable goals, e.g., efficiency and resilience, review practical urban problems under these goals, and explore the probability of using data-driven technologies as potential solutions to the challenge of complexity. On the basis of extensive urban data, we integrate urban problem discovery, operation of urban systems simulation, and complex decision-making problem solving into an entire cohesive framework to achieve sustainable development goals by optimizing resource allocation problems in complex cities.

INTRODUCTION

Our world is witnessing a rapid urbanization process. Estimates by the United Nations (UN) suggest that over 70% of the global population will reside in cities by 2050, contributing to more than 80% of the global GDP while accounting for more than 70% of global greenhouse gas emissions.[1] The dynamic interactions between constantly increasing city dwellers and urban resources are giving shape to a new form of cities,[2–4] those that have to constantly balance the positive and negative influences of economic, social, and ecological phenomena. For instance, unequal distribution of monetary resources causes economic crises, disrupting the financial pillar of cities and leading to social panic.[5] Unconstrained usage of energy resources produces substantial emissions, giving rise to climate change and environmental risks, e.g., droughts, floods, and storms.[6,7] In the face of these devastating events, modern cities urgently call for sustainable developments,[8] namely, efficient usage and allocation of urban resources to meet major economic, social, and environmental challenges,[9–11] aligning with the UN's Sustainable Development Goal (SDG) 11 "Making cities and human settlements inclusive, safe, resilient and sustainable."[1] In response to this need, both governments and scientists are advocating a unified urban science framework for urban sustainability.[2,12–17]

Urban science studies regard the city as a complex system that grows and develops based on a variety of forces.[18] Urban areas are characterized by a high degree of strong nonlinear interactions among their physical, social, economic, and ecological elements. For instance, citizens travel in the city, interacting with electricity, transportation, communication, and water networks, connecting with other individuals and forming the overall basis for a society. Complex cities are growing and self-organizing under these dynamic interactions,[19–21] requiring accurate predictions and decisions to achieve sustainability. The resilient behaviors of urban areas during the recent pandemic and natural disasters have also witnessed the complexity of cities. The unique feature of complex cities is that they are dynamic, interdependent, and nonlinear, which are qualities that are hard to solve with traditional urban science methods, proposing substantial challenges to urban sustainability. First, the dynamic and nonlinear properties of complex cities require efficient and effective solutions for urban sustainability. For example, the propagation of disturbances through the whole complex systems, and how cities are resilient to them, are difficult to model by simple statistical approaches, as seen in the COVID-19 pandemic's impact on health, social, and infrastructure networks.[18,22] Fast-changing demands and consumption behaviors necessitate new methods that can instruct the allocation of resources under an enormous search space of optimization.[23] Therefore, achieving urban sustainable developments requires multi-disciplinary, multi-scale, and multi-factor modeling, which goes beyond traditional urban studies. Second, traditional research relies on limited data. For instance, research on sustainable planning is often limited to a few urban land use cases,[24] and studies on energy consumption are constrained to non-representative households.[25] These challenges of complexity call for a paradigm shift for advancing global urban sustainability, which must tackle the dynamic, strongly interdependent, and nonlinear attributes appropriately.

Recently, the burgeoning availability of massive data from diverse urban sources has made data-driven approaches increasingly vital for exploring and addressing urban complexity.[26] Advances in computing, simulation, and decision-making within data science and artificial intelligence (AI) now allow researchers to probe complex systems in unprecedented ways.[27,28] For instance, data-driven methods can characterize complex interdependencies,[29] simulate long-term evolution of complex systems,[30] and further control and manipulate complex systems,[31] providing substantial opportunities for implementing data-driven methods toward achieving the sustainable development of complex cities. However, the design of data-driven methods still faces challenges. One major challenge is appropriately combining various urban data sources for discovering sustainable development problems in complex cities. This can be difficult due to multi-modal, multi-scale datasets, and insufficient missing data caused by the limited precision and granularity of sensing and observation technologies. Furthermore, developing sustainable solutions for complex urban challenges demands a systematic approach that encompasses problem identification, simulation of potential solutions, and implementation of effective decision-making strategies. Achieving this comprehensive pathway is intricate and necessitates enhanced research design that integrates diverse data-driven approaches, as opposed to the individual steps that they are typically addressed by existing methodologies.

In this review article, we provide an overview of current research progress on urban sustainability and conceptualize MetaCity, a unified framework that explores data-driven approaches to achieve sustainable developments

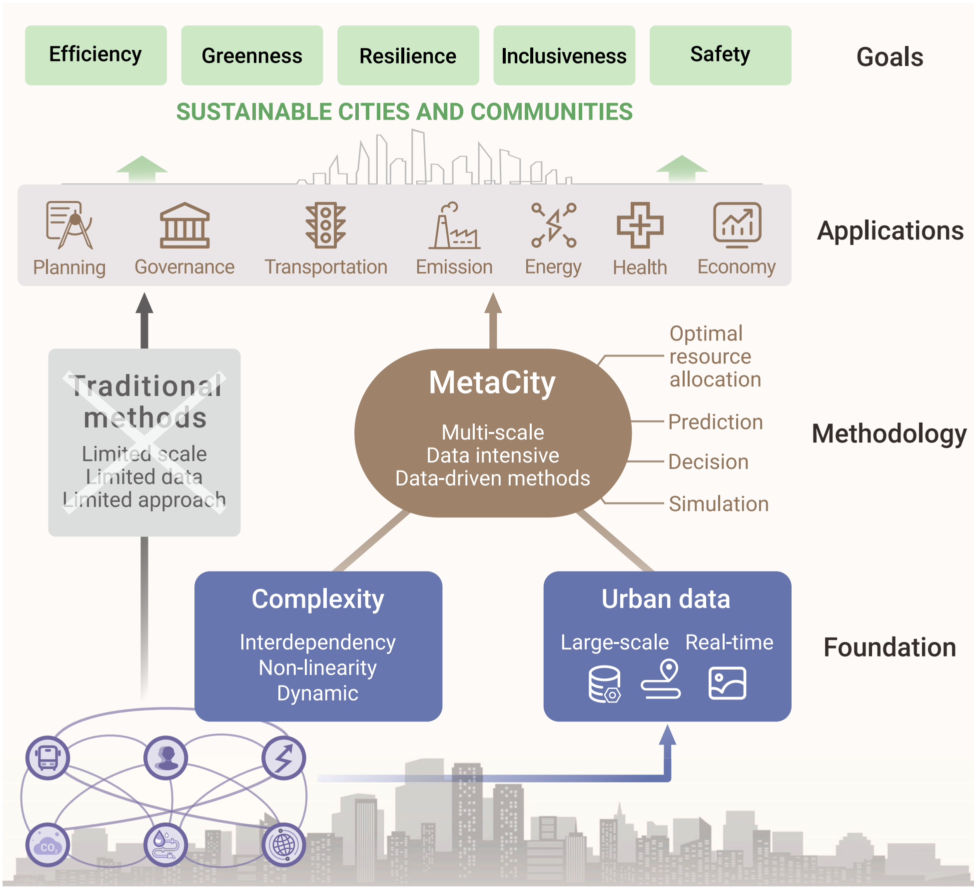

Figure 1. The overall framework of MetaCity Facing complexity challenges, the MetaCity framework utilizes large-scale urban data to develop data-driven methods that facilitate various applications aimed at achieving Sustainable Development Goals.

of complex cities (Figure 1). Governed by instructive SDGs, the complexity of urban environments poses significant challenges to optimizing limited urban resources. The large-scale urban data serve as the foundation of MetaCity, supporting the modeling of complex interactions in cities. Within this framework, researchers use urban data to investigate complex problems, simulate operations of urban complex systems, and test the impacts of various solutions on complex decision-making processes, thereby facilitating optimal resource allocation and various applications that support sustainable developments in urban systems. The purpose of this paper is to present a novel pathway to achieving urban sustainability by addressing the challenges posed by complexity as a pivotal breakthrough. The MetaCity framework has the potential to assist cities in making well-informed decisions and optimizing resource allocation more effectively, thereby bearing substantial implications for SDG 11 across diverse perspectives including urban planning, energy, public health, economy, etc.

The remainder of this review article is organized as follows. Core idea and fundamental problem synthesizes the core concept and research challenges of the MetaCity framework. Goals of sustainable urban development under MetaCity summarizes five potential SDGs within the MetaCity framework. Featured methodology of MetaCity reviews the key methods employed within MetaCity to address SDG challenges. Applications of MetaCity provides specific case analyses with empirical data and highlights key potential applications under the MetaCity framework. Challenges and future directions explores open questions and envisions future directions for research. Finally, the conclusions are summarized.

CORE IDEA AND THE FUNDAMENTAL PROBLEM

A city is a complex system that involves miscellaneous resources, e.g., land, roads, electricity, and water.[32] Equipment such as machines or vehicles in the city compete for the resources to function normally, and humans compete for these resources to achieve higher living standards. While the urban population is growing fast in various locations worldwide, the resources in cities are always limited and sometimes non-renewable. Therefore, the ultimate problem for a city is how to use limited resources to meet the needs of the present without compromising the ability of future citizens to meet their own needs, i.e., urban sustainable development.

However, as mentioned above, the complexity of the city presents considerable challenges when discussing resource allocation. The dynamic and nonlinear nature of urban systems means that the independent optimization of a single kind of resource for a single component can lead to unwanted outcomes in other components at other times, which cannot be resolved without introducing complex systems theories such as operations research, cybernetics, chaos theory, and dissipation theory, etc. In response to this urgent need, *MetaCity* framework is proposed, aimed at using the power of computing on massive *urban data* to solve the *complexity* of resource utilization and allocation for *sustainable development*. The ability to realize such a framework comes from the increasing amount of urban data available, which enables techniques such as statistical modeling, machine learning, and real-time simulation.

The name "MetaCity" comes from our expectation that this framework can transcend traditional understandings of complex cities to achieve SDGs. Since Patrick Geddes introduced the theory of evolution to urban planning over 100 years ago,[33] the idea that a city is a living organism capable of evolution has inspired innumerable insights and converged on the complexity theory of cities in the early 21st century.[34] The prefix "Meta-" signifies our aim to understand cities not only at the surface level but also to uncover the underlying dynamics and interconnections that shape their functioning. We consider the city to be a living organism, wherein MetaCity can highly optimize coordination and solve complex problems with a developmental perspective through rational analysis, thereby bringing about urban intelligence and a sustainable future.

For the core idea of the MetaCity framework (Figure 2), sustainable development serves as the primary goal and scope that motivates the initial idea, urban data provides the essential opportunity and foundation to conduct relevant research, and the complexity of the city highlights where the main challenges lie and shapes the solution.[35] Therefore, the framework is realized through the interaction of these three concepts. Utilizing massive urban data can allow us to discover existing or potential problems for urban sustainable development, thereby serving as our main research interest. The need for sustainable development leads to an emphasis on resource allocation under complex systems, which is the primary theme of the research content in MetaCity. Furthermore, to respond to the complexity of massive urban data, data-driven approaches are accentuated as the main methods of the framework. Therefore, MetaCity is a unified framework for optimizing the utilization and allocation of urban resources in complex cities through data-driven approaches to ensure sustainable development.

The research object and scope of MetaCity

Taking into account urban sustainable development as the ultimate goal, we dedicate special emphasis on the variety of urban resource needs. MetaCity takes urban resources as the primary research object, including but not limited to land, roads, housing, electricity, food, water, and minerals. Sustainable development emphasizes "meeting needs of the present without compromising the ability of future generations to meet their own needs" so that MetaCity will be concerned with issues directly related to resource allocation and utilization: where

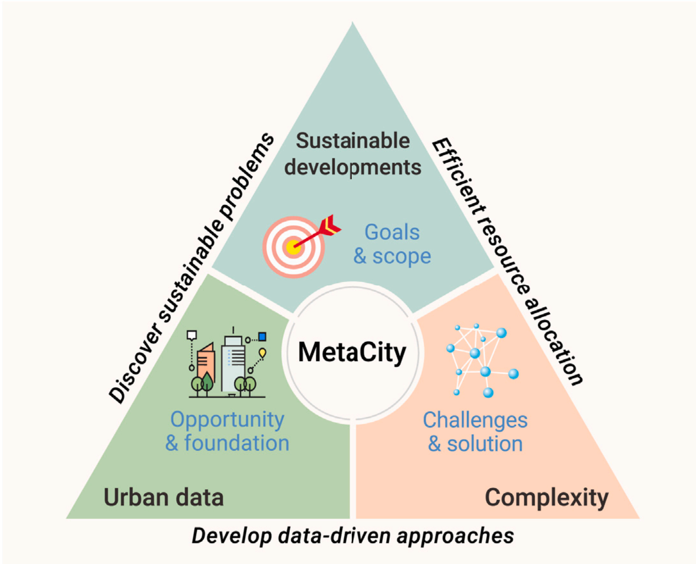

Figure 2. Core idea of the MetaCity framework Under Sustainable Development Goals in complex cities, the MetaCity framework emphasizes the utilization of urban data and data-driven approaches to discover and solve resource allocation problems.

are the existing resources, what are the existing needs, whether the current resource allocation meets the needs, and whether the current situation is sustainable? While allocation and utilization of resources are placed at the core of the framework, the acquisition, flow, exchange, and regeneration of urban resources should also be included to provide a full picture. Considering that the processes of resource allocation are often closely related to human activities, we also take into consideration human activities related to generating, distributing, exchanging, and consuming urban resources. Generally speaking, the framework is developed around allocating and utilizing urban resources and expanded to other related aspects.

We emphasize that the scope of MetaCity is not limited to academic discovery but also includes practical applications critical for urban sustainability. For instance, the famous Boston Big Dig Project[36] that consumes extremely large resources is an extreme case. The project cost 22 billion US dollars and 450,000 cubic meters of cement, enough for three round-trip pedestrian pavements between San Francisco and Boston, showing what happens in practice if an urban project is not adequately planned and assessed. Therefore, MetaCity proposes to discuss two kinds of problems: city science problems and urban computing problems. The former problems focus on revealing the laws of urban operation, while the latter problems focus on making accurate real-time predictions and decisions for sustainable development. The strong connection to practice ensures that the framework brings tangible improvements to urban life.

The essential difference between MetaCity and traditional urban science research

As an emerging framework, MetaCity has several essential differences compared with traditional urban science research, which arise directly from the approach toward complexity and the abundance of urban data.

Multi-modal data-driven methods for complex cities. As a complex system, almost every problem in a city involves multiple processes. For instance, traffic optimization involves the consideration of the urban function zones, traffic flow, road network, pedestrians, and environmental protection. Thus, resolving these city problems needs comprehensive consideration of multiple aspects and deep investigation into the corresponding data.

Traditional urban research and management are largely based on pre-defined assumptions and theories. Generally, city managers and researchers predict the short-term and long-term evolution of cities, and make decisions for cities according to classical physical laws. For instance, humans travel to different locations following the gravity law[37,38] and the attractiveness of urban locations follows Zipf's law.[38] On the one hand, these classical laws may fail to fit the real data under different scenarios due to their oversimplified assumptions. On the other hand, combining the laws from different aspects to solve a problem will introduce heavy compound errors.

Unlike traditional methods, MetaCity will utilize real multi-modal data rather than model-estimated data. Due to the aggregation of the vast amount of urban data, it becomes possible that cities can be predicted, modeled, and managed better via massive data and computing. Compared with recent success in natural language processing and game fields, e.g., AlphaGo,[39] Gato,[40] ChatGPT,[41] city applications involve multi-modal data and modeling of much more complex mechanisms.

Scale changes the problems in complex cities. Different from other areas in which solutions to small-scale problems can be easily extended to large-scale problems, scale should be emphasized more. This is because the increasing scale will change the problem radically, and a small expansion could cause the emergence of unexpected behaviors as the scale increases.[42,43]

Traditional urban research and engineering are primarily based on the study of individual components, overlooking the nature of complexity within the urban system. For instance, traffic signal control has been investigated for decades in civil engineering. Previous studies have created many advanced single-intersection traffic signal control methods to minimize delay. However, when it comes to the problem of controlling one thousand correlated traffic signals, the problem is not only about minimizing the delay, but also about keeping the road network working normally. This requires many more factors to be considered, e.g., vehicle buffering and bottlenecks in the road network.

On this scale, the key question is to obtain the synchronized traffic observation from all intersections and make traffic signal operations, respectively. Even a basic traffic signal algorithm (e.g., dividing the green time according to the traffic ratio) can work decently given the observed data, again illustrating the importance of large-scale urban data. Therefore, MetaCity needs to leap beyond traditional reductionist approaches and embrace the emergent characteristics of complex systems. By incorporating prescriptive and generative models, MetaCity can effectively solve urban tasks at different scales, adapting solutions that are responsive to the unique dynamics and interactions of city environments.

Simulation and computing for complex cities. Conducting experiments directly on the whole city is usually either unfeasible or not worthwhile. Therefore, an effective method is to establish a model according to the actual urban environment and then use it to conduct experiments, compare different consequences, and choose feasible solutions.

Traditional urban research often fails to explore the ability of simulation methods fully. For example, coarser models such as cellular automaton are often used as the proxy for urban growth,[44,45] and simulation at the building level, e.g., energy consumption, is extrapolated out to represent the whole city.[46] Oversimplification of the urban context, failure to account for human-related factors, and lack of integrated approach for different components can all undermine the fidelity of the simulation.

MetaCity emphasizes the ability of urban computing and simulation. Machine learning, especially generative AI,[47] has greatly advanced models' expressive capabilities and enabled urban simulations closer to the urban context, such as the advancement by reinforcement learning in transportation flow[48] and traffic signal control.[49] Meanwhile, accurate and real-time urban data help to capture actual situations to calibrate simulations and develop strategies directly, e.g., the school closure triggering mechanism of COVID-19 based on city-level real data.[50] Advancement of computing power and infrastructure will shift the research paradigm, making accurate computing and simulation much more important in the near future.

GOALS OF SUSTAINABLE URBAN DEVELOPMENT UNDER MetaCity

As a complex system, realizing sustainable urban development involves various urban components, including people, housing, energy, transportation, ecology, healthcare, etc. Although the urban components involved differ, the core characteristics of sustainable requirements are highly interrelated, and the solutions are often similar. For example, the official outcome target of SDG 11.1 mentions safe and affordable housing and essential services, while Target 11.2 concerns safe, affordable, and accessible transport systems. Both targets can be used to describe the city's inclusiveness, and the potential solutions would include recommendations about appropriate resource tilting toward vulnerable groups. Considering the consistency between these targets, we summarize

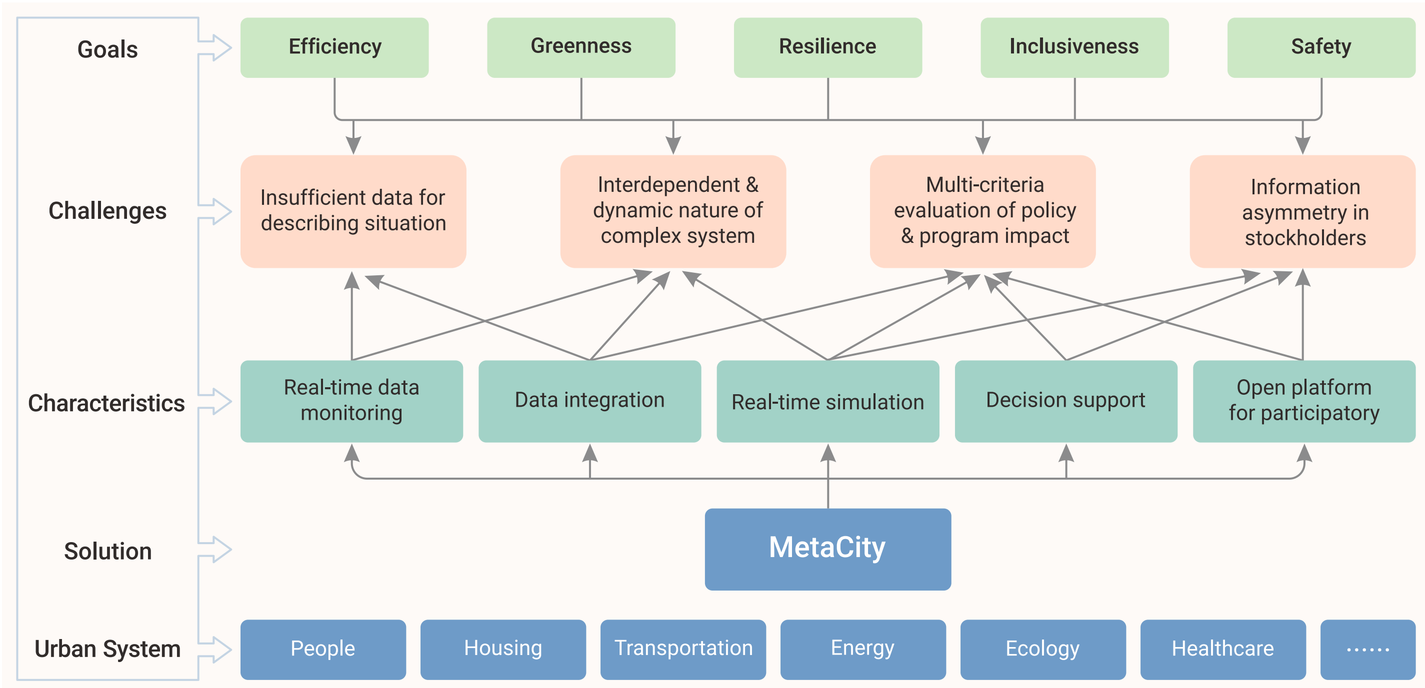

Figure 3. Goals of urban sustainable development and corresponding challenges that can be solved with MetaCity Building upon the characteristics and challenges of the MetaCity framework and urban data, five goals are extracted: efficiency, greenness, resilience, inclusiveness, and safety.

five main abstract goals across various urban components and sustainable targets: *Efficiency*, *Greenness*, *Resilience*, *Inclusiveness*, and *Safety*.

In implementing these abstract and interconnected goals, the city, a complex system with nonlinear and real-time responses, may experience many unexpected impediments. For example, urban greening projects often serve to improve the health of residents, but the spatial imbalance of greening caused by various conditions can also contribute to green gentrification and increase inequality and environmental injustice. Aside from such unexpected and unwanted results, similar predicaments could have also been raised in any other implementation stage, covering the situation description, impact evaluation, and reaching a consensus. MetaCity offers new possibilities to estimate the demand, and find and allocate resources that are both efficient and beneficial (Figure 3). We review the five main goals, analyze the challenges that they help to overcome, and the specific ways in which MetaCity can help.

Efficiency

Efficiency generally refers to the ability to accomplish a task or achieve a goal using the fewest of resources possible for the maximum output given an input. In sustainable urban development, as emphasized in SDG Target 11.b, efficiency means allocating urban resources effectively and efficiently to maximize production, minimize waste, reduce unfavorable impact, and ensure long-term viability.

Efficiency has been a long-standing focus in achieving sustainable urban development.[51,52] Various types of efficiency indicators and models have been developed to evaluate and compare the different kinds of urban efficiency, including land use,[53] natural resources,[54] energy efficiency,[55] transport policy,[56] etc. However, these analyses are often incomplete and limited, due to the quantity and timeliness of statistical data and complex mutual constraints among sectors.[57,58] Furthermore, it is usually hard to convince stakeholders to take practical actions for efficiency improvement under insufficient collaboration.[59]

Furthermore, MetaCity offers new possibilities to enhance efficiency in sustainable urban development. With emerging IoT technologies, acquiring, integrating, and analyzing tremendous heterogeneous urban data generated by sensors, vehicles, buildings, and humans can be made much easier. The rapid development of data-driven AI methods also enables the exploration of phenomena and rules in complex urban systems,[60] and the centralized platform enables communication and information sharing among different stakeholders by providing a comprehensive view of the situation and ensuring reliable real-time simulations.

Greenness

Modern cities consume vast amounts of energy and resources, generate a disproportionate amount of waste and pollution, and endanger the health and well-being of urban residents,[61,62] making greenness one of the core goals of sustainable urban development.[63] Although it is often used as the synonym for sustainability, the goal of greenness still shows conceptual specificity by viewing the urban environment as the main entry point for urban issues. Here, we examine two aspects involved in the greenness goal: the greening of urban space and the greening of urban life. The first one emphasizes providing accessible green space,[64,65] protecting urban ecological systems,[66–68] and retrofitting green infrastructure or nature-based solutions,[69,70] while the second one focuses on promoting clean production,[71,72] circular economy,[73,74] energy conservation,[75] and reducing pollution from production and consumption.[76,77] Both of these can result in the promotion of residents' health and well-being.

Some common vital steps exist despite considerable aspects and possibilities to reach the greenness goal. The first is to match the evidence and data across sectors and facilitate the integration of different indicators to develop linked indices for key sectors such as public space, transportation and energy.[78–82] Then comes the decision-making and priority setting based on health risk and environmental data, which aims to incorporate factors and disciplines that influence urban policy.[83–85] The last is to introduce community participation and integrate participatory procedures in policy formulation and implementation, essential to counter green gentrification for environmental justice.[86–88]

The MetaCity is of great importance in helping to achieve SDG Target 11.7 "provide universal access to green spaces." It can monitor real-time environmental data such as air and water quality, energy consumption, and waste management.[89] These data can then be used to make informed decisions on energy management, waste reduction, and resource utilization based on simulation. In addition, MetaCity can facilitate the integration of various data sources into the system, which means a lot in evidence and data match across sectors.[90] Finally, this technology also helps to promote an unbiased, open, and transparent participatory decision-making process under the premise of careful application of AI technology.[89,91]

Resilience

Considering the continuous increase in urban size, population diversity, and complexity, the potential damages from future extreme events and disasters increase proportionally. Besides natural disasters such as earthquakes, typhoons, and floods, cities face social-economic shocks such as economic crises, public health events, fires, and terrorist attacks.[92] Furthermore, the lack of infrastructure, insufficient food and clean water supply, and unemployment are all enduring challenges to cities, especially in developing countries.[93] These shocks and tensions put resilience at the heart of sustainable urban development.

Resilience refers to the ability of the system to resist, recover, adapt, and transform under external disturbances and pressure.[93–95] Mitigating the impact of disasters through land use planning and risk mitigation strategies constitute the complex framework of urban resilience,[96] including completing post-disaster recovery and reconstruction with the cooperation of local communities and government agencies,[97,98] and preparing for future hazards through transforming political structures and local social networks.[99,100]

Despite the broad coverage of urban resilience characteristics, few procedures and operational tools exist to evaluate and improve urban resilience in an integrated way.[94] When faced with emergencies, it is difficult to make reasonable resource allocation and emergency response without sufficient data and timely analysis as support.[101,102] Even after the shock, making an optimal repair plan based on intuition or simple principles for complex systems such as roads and power grids is almost impossible,[103–105] and the social awareness and institutional transformation needed to deal with chronic stress are also based on open and transparent evidence.[99,106]

MetaCity has special advantages in tackling these problems. Applying rich urban data to make early warnings and predictions before shocks is an essential manifestation of MetaCity on urban resilience, such as using remote-sensing techniques to predict landslides,[107] or using mobile phone data to early warning emergencies.[108] When a disaster occurs, the real-time collection and integration of urban data can also help relief organizations to monitor human movements and reach people in need quickly.[109] The AI-powered MetaCity can also provide real-time decision-making suggestions in simulated and actual scenarios through reinforcement learning and other methods.[110–113] Compared with traditional slow and time-consuming analysis and judgment by humans, such automated mechanisms are vital when dealing with emergencies that require rapid response[114,115] or in the face of complex and coordinated cascading systems.[116,117] Furthermore, MetaCity can give play to its optimization features for long-term land use planning[118–120] and short-term deployment of disaster relief materials,[121,122] promoting urban resilience without additional resource investment.

Inclusiveness

Inclusiveness is the first description of cities and communities in SDG 11 "make cities and human settlements inclusive, safe, resilient and sustainable." To ensure that cities can provide opportunities and better living conditions for all residents, it is essential to understand that inclusive cities mainly involve spatial, social, and economic factors.[123] Spatial inclusion refers to affording necessities such as housing, water, and sanitation, since access to essential infrastructure and services is a daily struggle for many disadvantaged households.[124] Social inclusion refers to equal rights and participation of all, including the most marginalized urban poor, which prevents incidents of social upheaval in cities.[125] Economic inclusion means creating jobs and allowing all urban residents to enjoy the benefits of economic growth.[126] It should be clear that, while the goal of resilience focuses on the robustness of the city's infrastructure and services, the goal of inclusiveness emphasizes social equity and the fair distribution of benefits across all communities.

To advance inclusiveness in cities means achieving a fair and equitable distribution of spatial, social, and economic resources, respectively. This includes the pursuit of fair distribution and utilization of resources and more emphasis on reasonable preference for vulnerable and underrepresented groups from the comprehensive perspective of history and social reality. A deep understanding of the conditions of urban residents and spatial configuration is necessary,[127,128] so as to increase the participation of local communities in the decision-making process and avoid subjective bias as much as possible.[129]

As a data-driven method, MetaCity can identify vulnerable populations and vulnerable communities by detecting their social-economic status through remote sensing and mobile phone data,[130,131] and can further analyze and understand their specific needs and challenges.[132–134] Importantly, in the design of MetaCity, it is crucial to incorporate public participation by integrating interfaces at the input stage, aligning with SDGs' emphasis on inclusive development. This requires a deliberate inclusion of public participation features in both the technological framework and institutional design to ensure that all community members, especially vulnerable groups, can contribute to and influence decision-making processes. On this basis, MetaCity can use predictive modeling to simulate the impacts of different policies and programs, helping to develop targeted ones and identify the most likely effective ones.[135,136] Moreover, MetaCity can facilitate community engagement and empowerment by providing platforms and tools that allow vulnerable groups to participate in decision-making.[137–139] By using such a data-driven and inclusive approach, MetaCity can help cities create more inclusive spaces for vulnerable groups, identify and address their specific needs and challenges, and provide opportunities for participation in decision-making processes.

Safety

Global studies show that 60% of all urban residents in developing countries have been victims of crime at least once over the past 5 years.[140] The increased crime, violence, and lawlessness during urbanization are exacerbated by corruption, the proliferation of weapons, substance abuse, and youth unemployment. These insecurity factors restrict urban social and economic development in return, constantly jeopardizing opportunities and future development, posing a challenge that will not be solved without a deliberate effort.

As UN-Habitat has pointed out in the Safer Cities approach,[141] crime and violence do not happen spontaneously, but are motivated by inadequate urban environments.[142] Namely, excluding some members of society from the benefits of urbanization is the economic origin of crimes.[143] At the same time, the lack of political participation and the failure to promote inclusive policies creates a breeding ground for social unrest.[144] Furthermore, criminal justice systems such as police, courts, and prisons play a crucial role in deterrence, but alone they cannot offer sustainable governance.[145] Urban safety must be considered a right for all, and the long-term solutions to these social, economic, and governance problems depend on partnerships between local governments and other stakeholders.[146]

The real-time monitoring of the urban environment provided by MetaCity is an excellent aid in preventing and fighting crime. Real-time monitoring of the occurrence of crime can help efficiently allocate police forces,[147] promoting alternative policing forms such as community policing,[148] significantly reducing the cost of tracking criminals,[149] and establishing effective deterrence to prevent crime.[150,151] On the other hand, upgrading projects in the urban physical environment, such as slum upgrading, is one of the pillars of urban crime prevention,[152,153] and can benefit a lot from the accurate and sufficient urban data provided by MetaCity.[154] Finally, community planning, managing urban streets and public spaces, and community appropriation can help promote social integration and citizenship values,[155,156] all of which depend on open and inclusive management and decision-making. MetaCity can provide an open participation approach, and expound and prove the effectiveness of various agendas, strategies, and activities with its sufficient data and powerful simulation capabilities.[157,158] Overall, MetaCity will be a powerful tool to achieve the goal of urban safety.

FEATURED METHODOLOGY OF MetaCity

The ability of the MetaCity framework to solve urban sustainable development problems is one of the core guiding principles of its methodology. Here, we introduce the advantage of data-intensive urban science techniques and review recent progress in data-driven urban computing methodologies for optimizing urban resources in complex cities.

Data-intensive urban science

The backbone of the MetaCity framework is the use of massive urban data and advanced analytical tools that extract laws and rules of cities from these data. Data-intensive urban science, MetaCity's first featured methodology (Figure 4), makes intense usage of various forms of real-time urban data to investigate urban problems. All further applications, including urban simulation, resource allocation, and sustainable decisions, are made based on data from various sources, including sensor data, social media data, remote sensing data, administrative data, web content, etc.[159,160] Thus, the framework needs to gather and store abundant data that can capture complex interactions and activities within cities as the basis of its application on urban sustainable development. Size as well as the dynamically changing nature of urban interaction data are key characteristics

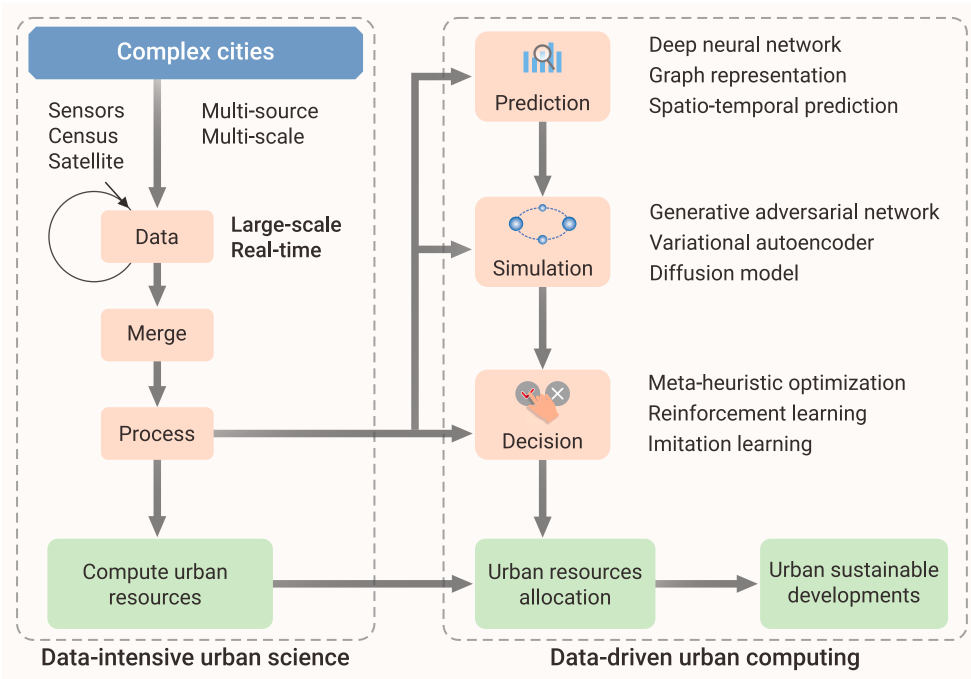

Figure 4. Featured methodology of MetaCity Data-intensive urban science emphasizes the use and processing of urban data from various sources and scales. Subsequently, methods under the data-driven urban computing paradigm solve urban resource allocation problems to achieve sustainability.

of data-intensive urban science. The credibility and quality of collected data are of great importance to solving urban sustainable development problems; therefore, researchers should seek data with high temporal and spatial resolutions, particularly real-time and online urban data to support the framework.[161–163] Real-time data, such as traffic flows, interactions on social media, air quality, and electricity consumption, all reflect the traces of urban functioning and the state of cities on their path to sustainable goals. Therefore, the update of real-time and large-scale urban data is an essential part of the MetaCity framework.

This data-driven approach allows MetaCity to discover real problems of resource usage and allocation in the city from collected real-time data, which consists of three stages. First, data of different temporal resolutions, spatial resolutions, and representation forms are stored and merged on an appropriate level. For instance, satellite image data are often recorded as RGB images of grids in cities under certain resolutions, while demographic and administrative data are collected based on administration areas defined by the government. These data should be aligned carefully and correctly in the quest for accurate estimations of urban resources. Second, merged data from various sources are processed with statistical tools. This stage includes feature extraction from mass trajectories and movement, graphic, audio, and video data, the transformation of time series data, the redistribution of demographic data on remote sensing grids, etc.[164,165] The processing procedure aims to provide more contextual information on the distributions and dynamics of urban resources. From the processed urban data, researchers can deduce urban laws that uncover the development and scales of cities. For instance, the law of human flows and mobility,[38] and the scaling laws of urban facilities. Finally, the processed data are utilized in data-driven urban computing tasks, which are discussed in the following section. In general, data-intensive urban science is the theoretical basis of the framework. We build a path linking multi-disciplinary real-time data from complex cities to inform urban computing tasks in practice.

Data-driven urban computing

The data-intensive urban science emphasizes the use of large-scale real-time urban data for urban sustainable development problems. Correspondingly, to solve these problems under the scenario of complex cities, appropriate data-driven urban computing methods are adopted in the MetaCity framework (Figure 4). Urban computing aims to learn reinforced knowledge from heterogeneous urban data efficiently with computational methods as the basis to provide urban services.[166] Here, we summarize three key classes of urban computing methods for addressing sustainable development problems in complex cities, namely prediction, simulation, and decision.

Prediction. Urban prediction tasks can be viewed as a procedure for the discovery of complex relationships in the city, such as how urban infrastructures are resilient to disasters and how pandemics spread throughout urban networks. One important urban prediction problem is the prediction of the unobserved amount of urban resources. For instance, retrieving the actual carbon emissions or the real total traffic on roads is time-consuming and thus inefficient. Estimations of these metrics based on easily collected data, including electricity and gas consumption, remote sensing data, and parking data, are feasible substitutes for downstream applications. However, accurate predictions are limited as urban resources are influenced by complex urban factors. Traditional estimation and prediction methods, such as time series forecasting and statistical regression models, are effective but are limited when applied to large-scale data or complex scenarios involving numerous interacting variables.[167] These traditional methods often struggle to capture the intricate, nonlinear relationships and dependencies that characterize urban systems.

Recent advances in deep learning have enhanced the accuracy and efficiency of urban prediction tasks, particularly in scenarios involving large datasets and complex variable interactions.[28,168] Deep neural networks, known for their ability to approximate complex functions, become central to urban prediction models. These networks are often combined with spatiotemporal prediction models, which are particularly vital in urban computing. Spatiotemporal models address the need to predict phenomena such as traffic flow, pollution levels, or weather conditions by capturing how these variables evolve over both space and time.[169–172] For instance, traffic prediction models utilize graph convolutional networks to represent the spatial structure of road networks, combined with recurrent neural networks (RNNs) or temporal attention mechanisms to model how traffic patterns change over time. These integrated models can handle diverse data sources, such as GPS data, traffic cameras, and historical logs, providing accurate, real-time predictions that inform urban transportation planning and congestion management. Transformer models, originally developed for natural language processing tasks, are adapted for urban prediction tasks due to their ability to handle long-term dependencies in data.[173–175] Unlike traditional RNN-based models, transformers rely on self-attention mechanisms that allow them to consider all parts of a sequence simultaneously, making them particularly effective for tasks that require understanding of long-range dependencies.[176] Using such deep learning algorithms, the MetaCity framework is able to achieve satisfying prediction performances on diverse urban sustainability problems.

Simulation. Merely predicting metrics of urban sustainable developments cannot provide a macro view of the problems, especially on important policy-making procedures. A step forward from prediction to the simulation of complex cities from real-world data is a promising solution to bridge this gap.[50,177] Mapping the operating laws of real complex cities into a simulation system can provide a flexible and open environment for decision-making issues such as subsequent policy formulation. Traditional simulation methods are restrained to small scales due to the lack of computational resources, making them incapable of being extended to complex city scenarios.[178]

Recent advancements in generative models have shown the power in generating languages, time series, human trajectories, etc., based on real-world observations while retaining basic characteristics.[47,179–181] Generative adversarial networks (GANs)[182] use a generator to create synthetic data and a discriminator to evaluate its authenticity, refining the output until it closely resembles real data.

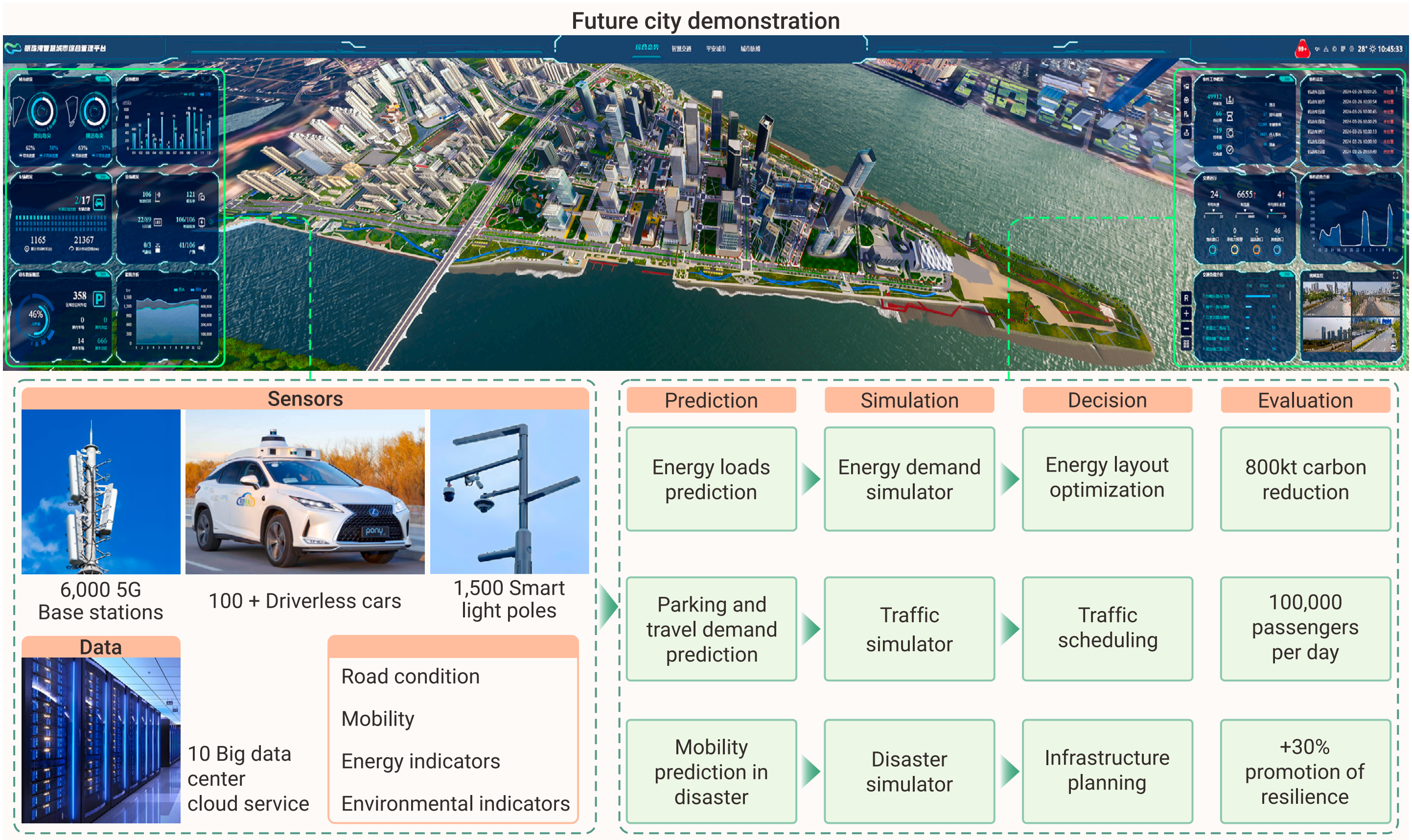

Figure 5. Demonstration of a real-world application of the MetaCity framework The future city project conducted in a new district in China exemplifies the application of the MetaCity framework. Leveraging large-scale urban data, the project employs data-driven methods to predict, simulate, and make decisions aimed at achieving Sustainable Development Goals.

Variational autoencoders[183] encode data into a latent space and then decode it to generate new variations, useful for simulating different urban scenarios. Generative adversarial imitation learning[184] combines GANs with imitation learning to model and replicate complex human behaviors based on real-world examples. On the other hand, diffusion models[185] iteratively transform random noise into structured data, producing high-resolution simulations that capture intricate real-world details.

Under the MetaCity framework, these models need further extension and permutations to fit the complex interactions within cities and the requirement of simulating data across various fields. Moreover, the simulated data should also be reliable enough to support the deduction of complex interactions in cities and the following decision-making processes.[186] Therefore, the data-driven simulation methods should be cross-scaled to fit the macro- and micro-level of cities and enhanced with knowledge of urban sustainable development to generate reliable reflections of real cities.

Decision. Built upon the simulation system of complex cities, MetaCity seeks to make decisions on optimizing the allocation of urban resources to achieve SDG 11. Values of decisions are affected by various complex interactions in cities. For instance, scheduling traffic signals based on the simulation of urban traffic flow to reduce waiting time and carbon emissions, controlling the supply of power grids to minimize costs while meeting generated household and industry needs, allocating healthcare resources to people with high affection risks during pandemics, and planning public transit and shuttle bus routes to accurately meeting travel demands. To enhance the decision-making process within the MetaCity framework, we propose a shift from traditional expert knowledge-driven optimization algorithms to data-driven methods. Traditional methods, such as meta-heuristic and mathematical optimization techniques, often struggle with complex systems due to the enormous search space and the need for simplification,[187] which can compromise accuracy and effectiveness.

The improvements made in reinforcement learning models[188] present the opportunity of optimizing long-term sustainable outcomes with sequences of decisions made by artificial agents. In reinforcement learning, artificial agents are trained to make decisions by interacting with their environment. The agents receive feedback in the form of rewards or penalties based on the outcomes of their actions, allowing them to learn and refine their strategies over time. This method is particularly suited for urban resource optimization because it enables the agents to focus on long-term sustainable outcomes rather than just immediate gains. For example, reinforcement learning has been successfully applied in many sustainable development problems such as healthcare resource allocation,[189] power grid control,[190] traffic light control,[191] urban planning,[192,193] etc. Imitation learning[194] is another key method that complements reinforcement learning by enabling agents to learn from expert demonstrations. Instead of learning solely through trial and error, imitation learning allows agents to observe and mimic the actions of human experts. This approach can significantly accelerate the training process and improve the performance of agents in complex urban scenarios. Typically, decisions and policies can be tested on the simulation system in the framework, reducing monetary and temporal costs. In this way, the featured methodology of MetaCity acts as a system ranging from data collection to decision-making as a whole.

APPLICATIONS OF MetaCity

Based on SDGs advocated in goals of sustainable urban development under MetaCity and MetaCity's advantageous methodology, we first provide two representative cases under the framework reflecting the featured methodology (Figure 5). Then, we elaborate on possible applications of the framework from seven perspectives, i.e., urban planning, urban governance, transportation, carbon emission, energy, public health, and economy. For each application, we discuss the multi-source urban data as the foundation of a MetaCity framework and possible data-driven methods that can be leveraged to solve urban sustainability problems based on existing research topics (Figure 6).

Representative cases

Mirage: City simulation framework. Decisions on urban sustainable development are difficult to evaluate before being implemented in the

Field	Data	Applications
Urban planning	• Land use data • Economic indicators • Human mobility	• Slum management • Urban service location • Urban spatial planning
Urban governance	• CCTV • Social media • Geographic information	• Waste management • Social opinion perception • Inclusive public participation
Transportation	• Real-time traffic speed • Surveillance videos	• Road traffic prediction • Traffic signal control • Congestion pricing
Carbon emission	• Annual emission • CarbonMonitor • NASA OCO-2	• Carbon emission prediction • Carbon emission simulation • Decarbonization policy-making • Efficient carbon capture
Energy	• Nighttime light • Electricity power consumptions	• Efficient electricity supply • Power grid simulation • Renewable resource allocation • Resilient network allocation
Public health	• COVID-19 cases • Electronic health records	• Health crisis prediction • Equitable resource allocation • Resilient health system construction
Economy	• Global trade • Local consumptions • Employment status	• Economic growth prediction • Economic policy-making • Poverty reduction

Figure 6. Potential applications of the MetaCity framework for urban sustainable developments We summarize important urban data and corresponding applications of MetaCity from seven typical perspectives of urban sustainability.

physical world. To address this, we introduce Mirage,[195,196] an efficient and extensive city simulation framework that provides a data-driven solution to decision-making in complex city environments. Based on distributed simulation systems and data-driven analytical tools, Mirage simulates the complex interactions between space (road, area of interest), humans (referred to as agents in the system), and objects (environment, infrastructures) in cities on a large scale. It leverages various machine learning methods enhanced with expert knowledge to efficiently simulate collected behavioral data on urban infrastructure networks, urban mobility, and traffic patterns. Specifically, based on learned patterns in the simulated city, its mobility module can simulate 900,000 agents (humans) simultaneously on the road network of Beijing, one of the world's largest cities, at within 200 ms per step. This high efficiency, combined with its API availability to real urban data input, can provide a real-time simulation of interactions in complex cities. Beyond conventional traffic simulation systems that mainly focus on urban traffic flows, Mirage considers agents' social needs, including their demand for water, electricity, communication, and mobility. The extensiveness of interactions between human and infrastructure networks in the simulation framework yields applications for urban sustainable developments, including urban vulnerability, disaster risk reduction, water supplies, power shortages, and sustainable transport. Researchers can test how their policies meet urban SDGs in Mirage for better decision-making procedures such as traffic light control.

Sustainable future city project. We provide a comprehensive demonstration of how the MetaCity framework operates in a real-world application (Figure 5). We take the future city project conducted in a new district in China as an example, which applies the idea of the MetaCity framework to build a green, efficient, and resilient city. In line with the featured methodology in Figure 4, the project comprises two main components: (1) data sensing and processing and (2) data-driven urban computing. As for the data sensing stage, in addition to data collected by traditional sensors embedded in factories and power plants, the project introduces 1,500 smart light poles equipped with intelligent sensors and cameras, as well as hundreds of driverless cars patrolling the district. These smart devices generate multi-modal data covering road conditions, vehicle and pedestrian mobility, energy consumption, and environmental indicators, etc., which are stored and processed in big data centers.

Based on the data foundation, the project implements data-driven methods to achieve following three SDGs: greenness, efficiency, and resilience. At the prediction stage, it employs spatiotemporal deep learning methods to comprehensively model the complex spatial and temporal interactions within the city. Specifically, it accurately predicts short-term operational demand as well as long-term development demand patterns for various energy types, including electricity, hydrogen, and solar energy, using an autoencoder network that separates different time scales.[197] In addition, based on data sensed by driverless cars, a graph neural network[198] is applied to model the spatiotemporal mobility patterns of vehicles and pedestrians, predicting their future locations and travel demands. Furthermore, the project utilizes a graph neural ordinary differential equations network[199] to predict the impact of disasters on human mobility and the condition of crucial infrastructure within the district.

The project then develops a comprehensive urban simulator that integrates elements across various aspects, including people, infrastructure, energy, transportation, the environment, etc., to generate the behaviors of city elements and their interactions. An energy simulation module generates hourly demands for five energy types under different development scenarios with a relative error less than 1.0%. Variational autoencoders[179] and diffusion models[200] are implemented to simulate the trajectories of over 100,000 vehicles and 200,000 pedestrians throughout the entire district. The urban simulator also includes a disaster module to analyze the impacts of typhoons and floods on individual housing and key infrastructure.[201]

With the accurate simulation of urban dynamics under specific scenarios, the project employs data-driven decision-making methods to achieve sustainability goals. A multi-scale energy layout optimization algorithm is used to plan the operation of 10 energy stations within the district. By redistributing energy across regions with heterogeneous demand, these energy stations achieve an annual reduction of 800 kilotons in carbon emissions. In addition, deep reinforcement learning algorithms are integrated into the urban simulator to optimize traffic and parking resources,[191] and to efficiently allocate driverless vehicles and hydrogen-powered buses to meet travel demands within the district. The driverless public transit system is capable of transporting over 100,000 passengers each day. For the resilience goal, nature-based solutions are implemented to redesign the layout of key infrastructure and land-use types,[193] as well as to construct disaster prevention facilities such as public shelters and seawalls. The overall resilience of the district is enhanced by over 30%.

Potential applications

Urban spatial planning. More than 56% of the population lives in cities today, and reasonable urban spatial planning plays a critical role in providing adequate and accessible housing and service provision. However, the imbalance of rapid economic development and the neglect of planning in urban sprawl gives rise to many slum communities[202] and leads to segregation, crime, education, health, and environmental problems.[203] Compared with traditional approaches, the MetaCity framework has the potential for planning cities and rearranging urban resource that simultaneously cover multiple goals.[204–206] Important factors that produce slums include the urban economy, the supply of land, and changes in real estate prices, and the inefficiency of previous proactive planning in preventing slums is due to the lack of prior knowledge of slum development and drivers.[207,208] MetaCity's integration of land use and economic data[209,210] provides a chance to predict and simulate the development of slums as a basis for optimizing economic benefits. On the other hand, human mobility data are crucial for assessing accessibility to urban resources. Through predicting and analyzing mobility patterns, MetaCity can enhance the accessibility of essential services such as food,[211] healthcare,[212] and education.[213] This analysis aids in strategically positioning urban services to mitigate slum-related issues.[214] Given these applications, MetaCity has the potential to utilize demographic, land use, mobility, and economic data to address not only slum conditions but also broader urban spatial challenges such as urban exodus and green gentrification, aligning with SDG Target 11.1's emphasis on improving housing and upgrading slums.

Urban governance. It is widely believed that smart city technology can be a possible solution for the population pressures faced by developing cities to meet the rising demand for services and infrastructure.[215–217] This is mainly achieved by making use of closed-circuit television and government data in urban governance fields such as traffic control, police management, and government services, which is also the field that has gone the farthest in the practice of MetaCity.[218–220] However, it has some very promising but not yet fully explored possible applications in urban governance. First, the powerful computer vision capabilities cannot only be applied to traffic and public security but also provide direct information about the status of urban ecosystems,[221] thereby providing assistance for factory production,[222] waste management,[223] etc. For instance, MetaCity can link real-time information on waste, recycling stations, and logistic vehicles to match waste processing needs and logistic vehicles, reducing the adverse impact of cities made by waste (SDG Target 11.6). Secondly, based on the massive data of social media with geographic information such as POI, the administrators would be able to perceive the opinions and emotions of residents through MetaCity, and provide precise and targeted responses and services.[224–226] Finally, the framework can facilitate community engagement and empowerment by providing platforms and tools that allow vulnerable groups to participate in decision-making, as emphasized in SDG Target 11.3.[227,228] For example, MetaCity can create digital media that will enable residents to give feedback on proposed policies and programs or to participate in virtual town hall meetings.[229] By using a data-driven and inclusive approach, the framework can help cities create more inclusive spaces for vulnerable groups, identify and address residents' specific needs and challenges, and provide opportunities for participation in decision-making processes.[230]

Transportation. Traffic congestion has been a major barrier preventing the efficiency of cities from being improved. The literature mainly covers traffic prediction and traffic policy making to enhance sustainable transportation, as advocated in SDG Target 11.2. Under the framework of MetaCity, studies on traffic prediction aim to provide accurate predictions in future time intervals and/or unobserved locations. Thus, they either organize the data as a grid or graph and apply machine learning models, including deep neural networks,[231,232] clustering model,[233,234] and boosting methods.[235] These studies mainly utilize the spatial dependency of locations that are neighboring each other on the graph, and the temporal dependency of time intervals adjacent to each other or occupying similar time points on different days. Currently, analysis under the MetaCity framework makes accurate predictions up to the scale of hundreds of intersections.[236] This has provided a basis for quick sensing and discovery of traffic congestion, and further policy making to improve traffic efficiency. Traffic policies, including traffic signal control,[191] congestion pricing,[237] and restriction policies,[238] have been long investigated to build a sustainable and efficient transportation system. Traditional methods usually assume that the traffic flow follows a pre-defined pattern, and then convert the policy making as an optimization problem. These methods perform poorly when dealing with the dynamic and increasingly large traffic flow. Hence, MetaCity research proposes reinforcement learning-based methods to work on these problems, due to their characteristics of directly learning from data rather than relying on assumptions. These newly innovated methods have demonstrated performance that exceeds traditional methods in various scenarios and are expected to bring more intelligence to related problems.[191]

Carbon emission. Carbon emissions are a major contributor to climate crises, especially global warming.[239] The world is still far from achieving the Paris Agreement's goal of reducing global warming, calling for urgent and strict control on current carbon emissions generated from human activities.[240,241] According to the World Bank, cities account for over 70% of global carbon emissions, indicating the key role of cities in the road to net zero emission.[242] Novel technologies such as carbon capture, utilization, and storage are fundamental solutions to sustainable carbon emission, which should be guided under data-driven methods to enhance efficiency.[243] The MetaCity framework can be leveraged for managing carbon emissions to achieve the *Greenness* goal. First, there are extensive data to support the data-intensive urban science on carbon emission. Urban carbon emissions can be divided into various sectors, including electronic generation, road transportation emissions, fossil fuel emissions, industrial emissions, aviation emissions, and residential emissions.[162,244] Annual carbon emission data are provided by most countries.[245,246] By contrast, real-time and high-resolution carbon emissions of each sector are mostly derived from other sources such as real-time power generation data, transportation congestion data, natural gas consumption data, and industrial consumption data. Another important resource is satellite data, for instance, NASA's OCO-2 and OCO-3,[247] and China's TanSat,[248] etc., collect data on atmospheric carbon dioxide. On the basis of these data sources, urban computing methods can be adopted for carbon accounting and monitoring.[249] Extensive studies have attempted to estimate real-time carbon emission data from power data.[162,250,251] However, current estimation of carbon emissions mainly relies on empirical algorithms that transform other data sources into the amount of emission. Following the guidance of the MetaCity framework, data-driven machine learning methods have the potential to calibrate the expert knowledge with high predictability when combined with atmospheric carbon dioxide data, which can be applied to discovering high-emission sites and sectors. Furthermore, based on real-time high-resolution emission information, decarbonization policies could be learned from data-driven optimization methods to identify the most efficient ways to conduct carbon capture technologies and shift to renewable energy sources.[252] Furthermore, the learned relationship between emissions and urban transportation could be used to guide transportation legislation such as traffic restriction policies,[253–255] aligning with the ambitions of the Paris Agreement and the Sendai Framework.

Energy. The UN's SDG 7 "Ensure access to affordable, reliable, sustainable and modern energy for all" pursues an equitable allocation of energy resources in the world.[256] The MetaCity framework can be adopted for energy management to achieve all goals. The inequality of energy accessibility is revealed from energy consumption data in most countries, indicating that the lights in some underdeveloped countries are "going out."[257] Global investments in electricity supplies and renewable resources are strongly interacting with the current usage of energy resources.[258] Under the MetaCity framework, data-driven methods such as time series prediction could model these interactions and possibly evaluate the effect of investments on filling the gap, for instance, to what extent can shifting a one billion dollar investment from the most developed countries to least developed countries enhance the deployment of clean and reliable energy in these countries. In addition, newly deployed renewable or traditional energy systems should take network resilience into consideration, particularly those in high-poverty developing countries that may be more vulnerable to natural shocks.[259] Research on the resilience of electricity systems has pointed out ways to build a complex system with topological structures robust to disturbances.[260] Here, we propose to improve these methods with data on the demographic and socioeconomic status of urban areas, providing more details on their vulnerability.[261] Models that are aware of these features could possibly simulate the dynamics of complex energy systems with higher accuracy, serving as the basis of targeted energy management decision-making for improving energy efficiency as advocated in SDG Target 7.3.

Public health. The serious consequences of the COVID-19 pandemic have brought unprecedented concern about the sustainable development of public health. The shock impact it had on the public health system also calls more attention to the existing concern over non-communicable disease.[262] Furthermore, the pandemic brings about mental health issues that remain long after it has ended. Over 90% of countries have included mental health support in COVID-19 response plans.[263] These interconnections depict a complex urban public health system that links the physical environment, health indicators, and psychological responses.[264] The MetaCity framework should be built on extensive public health data to support a sustainable public health system by accurate predictions of health crises, allocation of medical resources for healthcare equity, and building resilient and equitable medical systems. At present, digitalized healthcare systems generate useful electronic health records, whereas wearable devices and sensors collect environmental risk data such as air quality and pollution.[265–267] The literature on data-driven epidemic prediction has increased largely during the COVID-19 pandemic. Real-time infection case data are fitted by data-driven models that integrate expert knowledge and data knowledge, generating acceptable simulations of future infection trajectory.[268] Based on these simulations, data-driven optimization algorithms can be adopted for more equitable allocation of medical resources including vaccines and respirators.[269] These applications should be considered under specific scales, for instance, inter-city or intra-city resource allocation have different costs and social influence. Historical health record data and urban environmental data should be combined to build a resilient public health system that could operate well when facing unexpected healthcare demands,[270] especially in the post-pandemic era.[271]

Economy. Our world is still on the road to ending poverty.[272] The unequal distribution of wealth is exacerbated by the COVID-19 pandemic, highlighting the severe poverty in the least developed countries.[273] Moreover, economic activities are disrupted during the pandemic, leading to an economic recession that threatens countless households.[274,275] These negative economic trends are derived mostly from multi-scale open economy data provided by governments of different levels, providing a chance to construct a MetaCity framework for economic simulation and decision. Economic outcomes in cities have complicated interactions with many aspects, including social contacts, transportation, consumption, lockdown, employment, land use, the vigor of urban activities, etc.[276,277] Modeling the complex relations among urban planning data, urban social interaction data, and economic indicators by data-driven learning methods can help the evaluation of the economic impacts brought by urban policies and projects[278] and the selection of development paths.[279,280] This knowledge can support decisions made by economic experts in promoting economic equity and economic growth. One potential challenge of monitoring and boosting economic growth is the lack of economic evaluation in developing countries.[281] MetaCity research provides data-driven prediction and data generation tools to obtain economic indicators from other data sources, such as satellite pictures and street view images.[282] Combined with historical construction conditions, understanding of consequences of allocating urban resources to economic growth and poverty reduction could further contribute to the elimination of poverty in developing countries.

CHALLENGES AND FUTURE DIRECTIONS

The MetaCity framework poses many promising applications in multiple areas of urban sustainable development. However, large-scale implementation and deployment of MetaCity still face several concerns and challenges. In this section, we outline the major challenges and suggest directions for future work.

- Data security and privacy. MetaCity relies on large-scale data sharing and processing, which raises ethical concerns about data security and privacy. Open and prompt urban data are provided by diverse stakeholders including business agencies, companies, governments, research groups, and other groups. How multiple stakeholders reasonably share their respective data, especially individual data, is an important issue that requires careful consideration. Moreover, data collected from public spaces, such as CCTV surveillance to deter crime, may pose challenges to privacy and human rights protection.[283] The integration and overlay of various data sources to construct a comprehensive urban data network further complicates these issues, introducing new and open challenges. Some recent implementations propose building a central data governance protocol in MetaCity, where data are conceptualized as elements that flow through the system but never hold by any stakeholder accessing it. The central protocol also needs to manage and supervise any offline and online data access. In summary, as urban problems become increasingly data-driven, ensuring that data governance protocols evolve to meet data privacy challenges is essential for maintaining public trust and safeguarding the rights of all stakeholders involved.
- Limitation in key assumptions. One of the core assumptions of the MetaCity framework is the availability and accessibility of data. MetaCity assumes that large-scale urban data can be readily obtained from various sources in a timely, accurate, and comprehensive manner. However, in reality, the availability of such data may be constrained by factors such as proprietary restrictions, privacy concerns, and inconsistent data collection practices across different regions. Moreover, the quality and scale of data may be limited, particularly in smaller cities with less-advanced technological infrastructures. Limited data access and variability in scale can lead to reduced prediction accuracy and an increased vulnerability to bias, such as overlooking critical factors in urban dynamics, as well as deficiencies in providing real-time responses to urgent urban incidents. To address these challenges and implement MetaCity in smaller or less-developed cities, researchers could pre-train data-driven models on large-scale datasets from major cities and transfer the knowledge to smaller cities through fine-tuning strategies to achieve reasonable performance.[284] Generative models can be applied for data augmentation, while real-world feedback can be incorporated during the framework's operation to support continuous learning. In addition, integrating data-driven methods with expert knowledge could help build hybrid models that enhance the framework's applicability. Another key assumption of MetaCity is that all urban sustainability challenges can be addressed through data-driven methods. However, certain challenges may require more nuanced approaches that incorporate human judgment, cultural factors, and political considerations—elements that data alone may not fully capture.[217] Therefore, MetaCity research should be carefully assessed or supplemented with human expertise when applied to real-world problems.
- Trustworthy data-driven methods. From the perspective of the data-driven methods, MetaCity frameworks require effective and reasonable algorithms to solve the problem of urban sustainable development. As mentioned above, traditional methods are difficult to adapt to the data-intensive characteristics and complexity of MetaCity, calling for combinations with new technologies in the fields of AI and machine learning. Particularly, AI algorithms for sustainable development problems should have a certain degree of interpretability, or be trustworthy[285] for any practical applications on urban policies. Moreover, these algorithms can be biased due to deficiencies in data representativeness, where the accuracy of data concerning vulnerable groups may be questionable, leading to over-fitted decisions that favor the majority group. This requires strict regulation of data collection and policy formulation from authentic and comprehensive data. Furthermore, as urban sustainable development problems are unique in specific places, the reproducibility and applicability of algorithms under the MetaCity framework for these spatial-temporal problems should be emphasized. Although the effectiveness of algorithms could vary, researchers should build an "applicability map" for their methods to be applied in broader cases.[286]
- System deployment. A promising future direction involves the development of MetaCity systems tailored to address urban sustainable development challenges. Given the unique characteristics of sustainable development issues in different scenarios, such as varying resource distributions, cultural backgrounds, and policies on data sharing and algorithms, there is a need for customized implementations of the framework. To enhance efficiency and reduce the cost of repetitive system construction, future research should focus on creating a unified backbone framework, for example, a system that can estimate urban resilience and vulnerability, and complement specific elements of different scenarios.
- Interdisciplinary collaborations. MetaCity presents valuable opportunities for fostering interdisciplinary collaboration. The framework has the potential to connect diverse urban factors, resources, and infrastructures, thereby bringing together researchers from various fields, including urban planning, transportation, energy, health, computing, and social sciences.[287] To maximize the benefits of this interdisciplinary approach, it is essential to establish a platform that facilitates communication and cooperation among these scholars. In addition, developing a new research paradigm within the MetaCity framework will be crucial to ensuring fair and productive collaborations, enabling researchers to reach a consensus on complex urban issues.

- New resources and innovative development. As cities continue to evolve, the resources that drive urban development will also change, necessitating innovative approaches to human dynamics and urban mobility.[288] Intangible assets, such as data, patents, knowledge, talent, beliefs, and values, are becoming increasingly important in shaping modern urban development. Future research should explore how MetaCity can be leveraged to effectively utilize these disruptive new resources, guiding cities in selecting the most appropriate paths for innovative economic and social development. This direction invites exploration into how MetaCity can remain a compatible and adaptive platform in the face of ongoing urban evolution.
- Integration with large language models (LLMs). Future research could explore how MetaCity can leverage the capabilities of LLMs to enhance urban decision-making and planning.[41,289] LLMs, with their ability to process and generate human-like text, can be integrated into MetaCity to facilitate more natural and effective communication between the system and its users. This could involve developing intelligent chatbots or virtual assistants that help urban planners, policymakers, and citizens interact with the MetaCity framework. LLMs could also assist in analyzing vast amounts of urban data, generating insights, and predicting trends that inform sustainable urban development strategies.[290]

Based on the above discussion, we advocate for different stakeholders, including researchers, policymakers, and communities, to take concrete actions within the MetaCity framework, fostering scientific research and collaborative efforts toward building sustainable cities.

CONCLUSION

In this review, we present a comprehensive review of the potential of data-driven methods to achieve sustainability goals in complex urban environments, advocating for adapting these methods under the proposed MetaCity framework. While proliferating urban data provide inconceivable opportunities toward sustainable goals, the complexity of urban interactions across various domains hinders the exact recovery of urban resources and efficient resource allocation, requiring careful integration of data sources and analytical tools under specific SDGs. The framework underscores the use of data-driven methods, including urban resource prediction, urban simulation, and urban decision-making methods for resource optimization, to address the challenge of complexity. We offer strong implications across multiple disciplines and also interdisciplinary research. We hope that our framework can stir up data-driven research on urban sustainability topics, contributing to the efficiency, greenness, resilience, inclusiveness, and safety of future cities.

REFERENCES

1. Nations, U. (2020). Goal 11: Make cities inclusive, safe, resilient and sustainable. https://doi.org/10.5040/9781509934058.0017.
2. Elmqvist, T., Andersson, E., Frantzeskaki, N., et al. (2019). Sustainability and resilience for transformation in the urban century. Nat. Sustain. ***2***: 267–273. https://doi.org/10.1038/s41893-019-0250-1.
3. Shi, K., Yu, B., Ma, J., et al. (2023). Impacts of slope climbing of urban expansion on global sustainable development. Innovation ***4***: 100529. https://doi.org/10.1016/j.xinn.2023.100529.
4. Batty, M. (2007). Model cities. Town Plan. Rev. ***78***(2): 125–151. https://doi.org/10.3828/tpr.78.2.3.
5. Milanovic, B. (2016). Income inequality is cyclical. Nature ***537***: 479–482. https://doi.org/10.1038/537479a.
6. Edenhofer, O., Pichs-Madruga, R., Sokona, Y., et al. (2011). Renewable Energy Sources and Climate Change Mitigation: Special Report of the Intergovernmental Panel on Climate Change (Cambridge University Press). https://doi.org/10.1017/cbo9781139151153.
7. Yang, W., Zhang, J., Hua, P., et al. (2023). Global framework for flood risk management under climate change and urbanization. Innov. Geosci. ***1***: 100009. https://doi.org/10.59717/j.xinn-geo.2023.100009.
8. Cheng, H. (2020). Future earth and sustainable developments. Innovation ***1***: 100055. https://doi.org/10.1016/j.xinn.2020.100055.
9. Anderies, J.M., Folke, C., Walker, B., et al. (2013). Aligning key concepts for global change policy: robustness, resilience, and sustainability. Ecol. Soc. ***18***: art8. https://doi.org/10.5751/es-05178-180208.
10. Xiao, H., Xu, Z., Ren, J., et al. (2022). Navigating Chinese cities to achieve sustainable development goals by 2030. Innovation ***3***: 100288. https://doi.org/10.1016/j.xinn.2022.100288.
11. Wu, X., Fu, B., Wang, S., et al. (2023). Three main dimensions reflected by national SDG performance. Innovation ***4***: 100507. https://doi.org/10.1016/j.xinn.2023.100507.
12. Acuto, M., Parnell, S., and Seto, K.C. (2018). Building a global urban science. Nat. Sustain. ***1***: 2–4. https://doi.org/10.1038/s41893-017-0013-9.
13. Keith, M., Birch, E., Buchoud, N.J.A., et al. (2022). A new urban narrative for sustainable development. Nat. Sustain. ***6***: 115–117. https://doi.org/10.1038/s41893-022-00979-5.
14. Zhou, W., Pickett, S.T.A., McPhearson, T., et al. (2021). Conceptual frameworks facilitate integration for transdisciplinary urban science. npj Urban Sustain. ***1***: 1. https://doi.org/10.1038/s42949-020-00011-9.
15. Roberts, P., Carleton, W.C., Amano, N., et al. (2024). Using urban pasts to speak to urban presents in the Anthropocene. Nat. Cities ***1***: 30–41. https://doi.org/10.1038/s44284-023-00014-4.
16. Guo, H., Huang, L., and Liang, D. (2022). Further promotion of sustainable development goals using science, technology, and innovation. Innovation ***3***: 100325. https://doi.org/10.1016/j.xinn.2022.100325.
17. Karvonen, A., Cvetkovic, V., Herman, P., et al. (2021). The 'new urban science': towards the interdisciplinary and transdisciplinary pursuit of sustainable transformations. Urban Transform. ***3***: 9. https://doi.org/10.1186/s42854-021-00028-y.
18. Bettencourt, L.M. (2015). Cities as complex systems. Institut. Appl. Econ. Res. Bras. ***10***: 217–236. https://doi.org/10.1002/9781119425540.ch11.
19. Haken, H., and Portugali, J. (2003). The face of the city is its information. J. Environ. Psychol. ***23***: 385–408. https://doi.org/10.1016/s0272-4944(03)00003-3.
20. Haken, H., and Portugali, J. (2016). Information and self-organization. Entropy ***19***: 18. https://doi.org/10.3390/e19010018.
21. Moroni, S., Rauws, W., and Cozzolino, S. (2020). Forms of self-organization: Urban complexity and planning implications. Environ. Plan. B Urban Anal. City Sci. ***47***: 220–234. https://doi.org/10.1177/2399808319857721.
22. Jiang, Q., Xu, Z., and Zhang, H. (2022). Global impacts of COVID-19 on sustainable ocean development. Innovation ***3***: 100250. https://doi.org/10.1016/j.xinn.2022.100250.
23. Silvestro, D., Goria, S., Sterner, T., et al. (2022). Improving biodiversity protection through artificial intelligence. Nat. Sustain. ***5***: 415–424. https://doi.org/10.1038/s41893-022-00851-6.
24. Badiu, D.L., Iojă, C.I., Pătroescu, M., et al. (2016). Is urban green space per capita a valuable target to achieve cities' sustainability goals? Romania as a case study. Ecol. Indicat. ***70***: 53–66. https://doi.org/10.1016/j.ecolind.2016.05.044.
25. Ugarte, S., van der Ree, B., Voogt, M., et al. (2022). Energy Efficiency for Low-Income Households (European Parliament). https://doi.org/10.1007/s12053-018-9619-7.
26. Wang, F., Yao, D., Li, Y., et al. (2023). Ai-enhanced spatial-temporal data-mining technology: New chance for next-generation urban computing. Innovation ***4***: 100405. https://doi.org/10.1016/j.xinn.2023.100405.
27. Xu, Y., Liu, X., Cao, X., et al. (2021). Artificial intelligence: A powerful paradigm for scientific research. Innovation ***2***: 100179. https://doi.org/10.1016/j.xinn.2021.100179.
28. Xu, Y., Wang, F., An, Z., et al. (2023). Artificial intelligence for science—bridging data to wisdom. Innovation ***4***: 100525. https://doi.org/10.1016/j.xinn.2023.100525.
29. Yabe, T., Rao, P.S.C., Ukkusuri, S.V., et al. (2022). Toward data-driven, dynamical complex systems approaches to disaster resilience. Proc. Natl. Acad. Sci. USA ***119***: e2111997119. https://doi.org/10.1073/pnas.2111997119.
30. Kobayashi, Y., Takayasu, H., Havlin, S., et al. (2022). Data-driven stochastic simulation leading to the allometric scaling laws in complex systems. Phys. Rev. E ***106***: 064304. https://doi.org/10.1103/physreve.106.064304.
31. Baggio, G., Bassett, D.S., and Pasqualetti, F. (2021). Data-driven control of complex networks. Nat. Commun. ***12***: 1429. https://doi.org/10.1038/s41467-021-21554-0.
32. Bettencourt, L.M. (2021). Introduction to Urban Science: Evidence and Theory of Cities as Complex Systems (MIT Press). https://doi.org/10.7551/mitpress/13909.001.0001.
33. Geddes, P. (1915). Cities in evolution: an introduction to the town planning movement and to the study of civics (Williams). https://doi.org/10.2307/1779702.
34. Batty, M., and Marshall, S. (2017). Thinking organic, acting civic: The paradox of planning for cities in evolution. Landsc. Urban Plann. ***166***: 4–14. https://doi.org/10.1016/j.landurbplan.2016.06.002.
35. Zhao, Y., Zhu, Z., Chen, B., et al. (2023). Towards parallel intelligence: An interdisciplinary solution for complex systems. Innovation ***4***: 100521. https://doi.org/10.1016/j.xinn.2023.100521.
36. Greiman, V.A. (2013). Megaproject Management: Lessons on Risk and Project Management from the Big Dig (John Wiley & Sons). https://doi.org/10.1002/9781118671092.
37. Ravenstein, E.G. (1889). The laws of migration. J. Roy. Stat. Soc. ***52***: 241–305. https://doi.org/10.2307/2979333.
38. Schläpfer, M., Dong, L., O'Keeffe, K., et al. (2021). The universal visitation law of human mobility. Nature ***593***: 522–527. https://doi.org/10.1038/s41586-021-03480-9.
39. Silver, D., Huang, A., Maddison, C.J., et al. (2016). Mastering the game of Go with deep neural networks and tree search. Nature ***529***: 484–489. https://doi.org/10.1038/nature16961.
40. Reed, S., Zolna, K., Parisotto, E., et al. (2022). A generalist agent. Trans. Mach. Learn. Res. https://doi.org/10.15607/rss.2020.xvi.076.
41. Brown, T., Mann, B., Ryder, N., et al. (2020). Language models are few-shot learners. Adv. Neural Inf. Process. Syst. ***33***: 1877–1901. https://doi.org/10.18653/v1/2022.emnlp-main.90.
42. Langton, C.G. (1990). Computation at the edge of chaos: Phase transitions and emergent computation. Physica D ***42***: 12–37. https://doi.org/10.1016/0167-2789(90)90064-v.
43. Zhang, J., Wang, S., Liu, Y., et al. (2022). Does having more sustainable communities bring better sustainability? Innovation ***3***: 100267. https://doi.org/10.1016/j.xinn.2022.100267.

44. Batty, M., and Xie, Y. (1994). From cells to cities. Environ. Plann. Plann. Des. **21**: S31–S48. https://doi.org/10.1068/b21s031.
45. Santé, I., García, A.M., Miranda, D., et al. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. Landsc. Urban Plann. **96**: 108–122. https://doi.org/10.1016/j.landurbplan.2010.03.001.
46. Abbasabadi, N., and Ashayeri, M. (2019). Urban energy use modeling methods and tools: A review and an outlook. Build. Environ. **161**: 106270. https://doi.org/10.1016/j.buildenv.2019.106270.
47. Wang, Q., Feng, Y., Huang, J., et al. (2023). Large-scale generative simulation artificial intelligence: The next hotspot. Innovation **4**: 100516. https://doi.org/10.1016/j.xinn.2023.100516.
48. Zhang, H., Feng, S., Liu, C., et al. (2019). CityFlow: A multi-agent reinforcement learning environment for large scale city traffic scenario. In The World Wide Web Conference, pp. 3620–3624. https://doi.org/10.1145/3308558.3314139.
49. Chu, T., Wang, J., Codeca, L., et al. (2020). Multi-agent deep reinforcement learning for large-scale traffic signal control. IEEE Trans. Intell. Transport. Syst. **21**: 1086–1095. https://doi.org/10.1109/tits.2019.2901791.
50. Liu, Q.-H., Zhang, J., Peng, C., et al. (2022). Model-based evaluation of alternative reactive class closure strategies against covid-19. Nat. Commun. **13**: 322. https://doi.org/10.1038/s41467-021-27939-5.
51. Yan, Y., Wang, C., Quan, Y., et al. (2018). Urban sustainable development efficiency towards the balance between nature and human well-being: Connotation, measurement, and assessment. J. Clean. Prod. **178**: 67–75. https://doi.org/10.1016/j.jclepro.2018.01.013.
52. Allam, Z., Bibri, S.E., Jones, D.S., et al. (2022). Unpacking the '15-minute city' via 6G, IoT, and digital twins: Towards a new narrative for increasing urban efficiency, resilience, and sustainability. Sensors **22**: 1369. https://doi.org/10.3390/s22041369.
53. Schiavina, M., Melchiorri, M., Freire, S., et al. (2022). Land use efficiency of functional urban areas: Global pattern and evolution of development trajectories. Habitat Int. **123**: 102543. https://doi.org/10.1016/j.habitatint.2022.102543.
54. Liu, Y., Lu, F., Xian, C., et al. (2023). Urban development and resource endowments shape natural resource utilization efficiency in Chinese cities. J. Environ. Sci. **126**: 806–816. https://doi.org/10.1016/j.jes.2022.03.025.
55. Yu, C., Long, H., Zhang, X., et al. (2023). Regional integration and city-level energy efficiency: Evidence from China. Sustain. Cities Soc. **88**: 104285. https://doi.org/10.1016/j.scs.2022.104285.
56. Liotta, C., Viguie, V., and Creutzig, F. (2023). Environmental and welfare gains via urban transport policy portfolios across 120 cities. Nat. Sustain. **6**. https://doi.org/10.1038/s41893-023-01138-0.
57. Kennedy, C., and Hoornweg, D. (2012). Mainstreaming urban metabolism. J. Ind. Ecol. **16**: 780–782. https://doi.org/10.1111/j.1530-9290.2012.00548.x.
58. Caputo, P., Pasetti, G., and Ferrari, S. (2019). Implementation of an urban efficiency index to comprehend post-metropolitan territories—the case of Greater Milan in Italy. Sustain. Cities Soc. **48**: 101565. https://doi.org/10.1016/j.scs.2019.101565.
59. Liu, G., Wei, L., Gu, J., et al. (2020). Benefit distribution in urban renewal from the perspectives of efficiency and fairness: A game theoretical model and the government's role in China. Cities **96**: 102422. https://doi.org/10.1016/j.cities.2019.102422.
60. Zheng, Y. (2017). Urban computing: Enabling urban intelligence with big data. Front. Comput. Sci. **11**: 1–3. https://doi.org/10.1007/s11704-016-6907-2.
61. Liang, D., Shi, L., Zhao, J., et al. (2020). Urban air pollution may enhance COVID-19 case-fatality and mortality rates in the United States. Innovation **1**: 100047. https://doi.org/10.1016/j.xinn.2020.100047.
62. Liu, T., Meng, H., Yu, M., et al. (2021). Urban-rural disparity of the short-term association of PM2.5 with mortality and its attributable burden. Innovation **2**: 100171. https://doi.org/10.1016/j.xinn.2021.100171.
63. Schaubroeck, T. (2017). Nature-based solutions' is the latest green jargon that means more than you might think. Nature **541**: 133–134. https://doi.org/10.1038/541133b.
64. Gill, S.E., Handley, J.F., Ennos, A.R., et al. (2007). Adapting cities for climate change: The role of the green infrastructure. Built. Environ. **33**: 115–133. https://doi.org/10.2148/benv.33.1.115.
65. Lee, A.C.K., and Maheswaran, R. (2011). The health benefits of urban green spaces: A review of the evidence. J. Public Health **33**: 212–222. https://doi.org/10.1093/pubmed/fdq068.
66. Pickett, S.T.A., Cadenasso, M.L., Grove, J.M., et al. (2011). Urban ecological systems: Scientific foundations and a decade of progress. J. Environ. Manag. **92**: 331–362. https://doi.org/10.1016/j.jenvman.2010.08.022.
67. Pickett, S., Boone, C.G., McGrath, B.P., et al. (2013). Ecological science and transformation to the sustainable city. Cities **32**: S10–S20. https://doi.org/10.1016/j.cities.2013.02.008.
68. Wu, X., Lü, Y., Zhang, J., et al. (2023). Adapting ecosystem restoration for sustainable development in a changing world. Innovation **4**. https://doi.org/10.1016/j.xinn.2023.100375.
69. Tzoulas, K., Korpela, K., Venn, S., et al. (2007). Promoting ecosystem and human health in urban areas using green infrastructure: A literature review. Landsc. Urban Plann. **81**: 167–178. https://doi.org/10.1016/j.landurbplan.2007.02.001.
70. Dorst, H., Van der Jagt, A., Raven, R., et al. (2019). Urban greening through nature-based solutions–key characteristics of an emerging concept. Sustain. Cities Soc. **49**: 101620. https://doi.org/10.1016/j.scs.2019.101620.
71. Hens, L., Block, C., Cabello-Eras, J.J., et al. (2018). On the evolution of "cleaner production" as a concept and a practice. J. Clean. Prod. **172**: 3323–3333. https://doi.org/10.1016/j.jclepro.2017.11.082.
72. Giannetti, B., Agostinho, F., Eras, J.C., et al. (2020). Cleaner production for achieving the sustainable development goals. J. Clean. Prod. **271**: 122127. https://doi.org/10.1016/j.jclepro.2020.122127.
73. Williams, J. (2019). Circular cities. Urban Stud. **56**: 2746–2762. https://doi.org/10.1177/0042098018806133.
74. Paiho, S., Mäki, E., Wessberg, N., et al. (2020). Towards circular cities—conceptualizing core aspects. Sustain. Cities Soc. **59**: 102143. https://doi.org/10.1016/j.scs.2020.102143.
75. Mi, Z., Guan, D., Liu, Z., et al. (2019). Cities: The core of climate change mitigation. J. Clean. Prod. **207**: 582–589. https://doi.org/10.1016/j.jclepro.2018.10.034.
76. Zhu, L., Hao, Y., Lu, Z.-N., et al. (2019). Do economic activities cause air pollution? evidence from china's major cities. Sustain. Cities Soc. **49**: 101593. https://doi.org/10.1016/j.scs.2019.101593.
77. Esmaeilian, B., Wang, B., Lewis, K., et al. (2018). The future of waste management in smart and sustainable cities: A review and concept paper. Waste Manag. **81**: 177–195. https://doi.org/10.1016/j.wasman.2018.09.047.
78. Shields, K., Langer, H., Watson, J., et al. (2009). European green city index. Assessing the environmental impact of europe's major cities. https://doi.org/10.4324/9781032665184-14.
79. Mori, K., and Christodoulou, A. (2012). Review of sustainability indices and indicators: Towards a new city sustainability index (csi). Environ. Impact Assess. Rev. **32**: 94–106. https://doi.org/10.1016/j.eiar.2011.06.001.
80. Akande, A., Cabral, P., Gomes, P., et al. (2019). The lisbon ranking for smart sustainable cities in europe. Sustain. Cities Soc. **44**: 475–487. https://doi.org/10.1016/j.scs.2018.10.009.
81. Saez, L., Heras-Saizarbitoria, I., and Rodriguez-Nunez, E. (2020). Sustainable city rankings, benchmarking and indexes: Looking into the black box. Sustain. Cities Soc. **53**: 101938. https://doi.org/10.1016/j.scs.2019.101938.
82. Wu, S., Chen, B., Webster, C., et al. (2023). Improved human greenspace exposure equality during 21st century urbanization. Nat. Commun. **14**: 6460. https://doi.org/10.1038/s41467-023-41620-z.
83. Artmann, M., Kohler, M., Meinel, G., et al. (2019). How smart growth and green infrastructure can mutually support each other—a conceptual framework for compact and green cities. Ecol. Indicat. **96**: 10–22. https://doi.org/10.1016/j.ecolind.2017.07.001.
84. Mueller, N., Rojas-Rueda, D., Khreis, H., et al. (2020). Changing the urban design of cities for health: The superblock model. Environ. Int. **134**: 105132. https://doi.org/10.1016/j.envint.2019.105132.
85. Debrah, C., Owusu-Manu, D.-G., Kissi, E., et al. (2022). Barriers to green cities development in developing countries: evidence from Ghana. Smart Sustain. Built Environ. **11**: 438–453. https://doi.org/10.1108/sasbe-06-2020-0089.
86. Roseland, M. (1997). Dimensions of the eco-city. Cities **14**: 197–202. https://doi.org/10.1016/s0264-2751(97)00003-6.
87. Calderón-Argelich, A., Benetti, S., Anguelovski, I., et al. (2021). Tracing and building up environmental justice considerations in the urban ecosystem service literature: A systematic review. Landsc. Urban Plann. **214**: 104130. https://doi.org/10.1016/j.landurbplan.2021.104130.
88. Anguelovski, I., Connolly, J.J.T., Cole, H., et al. (2022). Green gentrification in european and north american cities. Nat. Commun. **13**: 3816. https://doi.org/10.1038/s41467-022-31572-1.
89. Mahajan, S. (2022). Design and development of an open-source framework for citizen-centric environmental monitoring and data analysis. Sci. Rep. **12**: 14416. https://doi.org/10.1038/s41598-022-18700-z.
90. Jain, G., and Espey, J. (2022). Lessons from nine urban areas using data to drive local sustainable development. npj Urban Sustain. **2**: 7. https://doi.org/10.1038/s42949-022-00050-4.
91. Masik, G., Sagan, I., and Scott, J.W. (2021). Smart city strategies and new urban development policies in the polish context. Cities **108**: 102970. https://doi.org/10.1016/j.cities.2020.102970.
92. Tyler, S., and Moench, M. (2012). A framework for urban climate resilience. Clim. Dev. **4**: 311–326. https://doi.org/10.1080/17565529.2012.745389.
93. Ribeiro, P., and Goncalves, L. (2019). Urban resilience: A conceptual framework. Sustain. Cities Soc. **50**: 101625. https://doi.org/10.1016/j.scs.2019.101625.
94. Meerow, S., Newell, J.P., and Stults, M. (2016). Defining urban resilience: A review. Landsc. Urban Plann. **147**: 38–49. https://doi.org/10.1016/j.landurbplan.2015.11.011.
95. Pickett, S.T., McGrath, B., Cadenasso, M.L., et al. (2014). Ecological resilience and resilient cities. Build. Res. Inf. **42**: 143–157.
96. Wardekker, A., Wilk, B., Brown, V., et al. (2020). A diagnostic tool for supporting policymaking on urban resilience. Cities **101**: 102691. https://doi.org/10.1016/j.cities.2020.102691.
97. Rouhanizadeh, B., Kermanshachi, S., and Nipa, T.J. (2020). Exploratory analysis of barriers to effective post-disaster recovery. Int. J. Disaster Risk Reduc. **50**: 101735. https://doi.org/10.1016/j.ijdrr.2020.101735.
98. Safapour, E., Kermanshachi, S., and Pamidimukkala, A. (2021). Post-disaster recovery in urban and rural communities: Challenges and strategies. Int. J. Disaster Risk Reduc. **64**: 102535. https://doi.org/10.1016/j.ijdrr.2021.102535.
99. Meerow, S., and Newell, J.P. (2019). Urban resilience for whom, what, when, where, and why? Urban Geogr. **40**: 309–329. https://doi.org/10.1080/02723638.2016.1206395.
100. Wijsman, K., and Feagan, M. (2019). Rethinking knowledge systems for urban resilience: Feminist and decolonial contributions to just transformations. Environ. Sci. Pol. **98**: 70–76. https://doi.org/10.1016/j.envsci.2019.04.017.
101. Cariolet, J.-M., Vuillet, M., and Diab, Y. (2019). Mapping urban resilience to disasters–a review. Sustain. Cities Soc. **51**: 101746. https://doi.org/10.1016/j.scs.2019.101746.

102. Poku-Boansi, M., Amoako, C., Owusu-Ansah, J.K., et al. (2020). What the state does but fails: Exploring smart options for urban flood risk management in informal Accra, Ghana. City Environ. Interact. **5**: 100038. https://doi.org/10.1016/j.cacint.2020.100038.
103. Kyriakidis, M., Lustenberger, P., Burgherr, P., et al. (2018). Quantifying energy systems resilience—a simulation approach to assess recovery. Energ. Tech. **6**: 1700–1706. https://doi.org/10.1002/ente.201700841.
104. Liu, W., and Song, Z. (2020). Review of studies on the resilience of urban critical infrastructure networks. Reliab. Eng. Syst. Saf. **193**: 106617. https://doi.org/10.1016/j.ress.2019.106617.
105. Liu, Z., Chen, H., Liu, E., et al. (2022). Exploring the resilience assessment framework of urban road network for sustainable cities. Physica A **586**: 126465. https://doi.org/10.1016/j.physa.2021.126465.
106. Therrien, M.-C., Usher, S., and Matyas, D. (2020). Enabling strategies and impeding factors to urban resilience implementation: A scoping review. J. Contingencies Crisis Manag. **28**: 83–102. https://doi.org/10.1111/1468-5973.12283.
107. Casagli, N., Intrieri, E., Tofani, V., et al. (2023). Landslide detection, monitoring and prediction with remote-sensing techniques. Nat. Rev. Earth Environ. **4**: 51–64. https://doi.org/10.1038/s43017-022-00373-x.
108. Bagrow, J.P., Wang, D., and Barabási, A.L. (2011). Collective response of human populations to large-scale emergencies. PLoS One **6**: e17680. https://doi.org/10.1371/journal.pone.0017680.
109. Lu, X., Bengtsson, L., and Holme, P. (2012). Predictability of population displacement after the 2010 haiti earthquake. Proc. Natl. Acad. Sci. USA **109**: 11576–11581. https://doi.org/10.1073/pnas.1203882109.
110. Cavdaroglu, B., Hammel, E., Mitchell, J.E., et al. (2013). Integrating restoration and scheduling decisions for disrupted interdependent infrastructure systems. Ann. Oper. Res. **203**: 279–294. https://doi.org/10.1007/s10479-011-0959-3.
111. Ye, Q., and Ukkusuri, S.V. (2015). Resilience as an objective in the optimal reconstruction sequence for transportation networks. J. Transport. Saf. Secur. **7**: 91–105. https://doi.org/10.1080/19439962.2014.907384.
112. Shang, W.-L., Chen, Y., Li, X., et al. (2020). Resilience analysis of urban road networks based on adaptive signal controls: day-to-day traffic dynamics with deep reinforcement learning. Complexity **2020**: 1–19. https://doi.org/10.1155/2020/8841317.
113. Lin, Y., and Shen, Z. (2022). An innovative index for evaluating urban vulnerability on pandemic using lambdamart algorithm. Sustainability **14**: 5053. https://doi.org/10.3390/su14095053.
114. Djordjević, S., Butler, D., Gourbesville, P., et al. (2011). New policies to deal with climate change and other drivers impacting on resilience to flooding in urban areas: the corfu approach. Environ. Sci. Pol. **14**: 864–873. https://doi.org/10.1016/j.envsci.2011.05.008.
115. Henonin, J., Russo, B., Mark, O., et al. (2013). Real-time urban flood forecasting and modelling–a state of the art. J. Hydroinf. **15**: 717–736. https://doi.org/10.2166/hydro.2013.132.
116. Hong, S., Lv, C., Zhao, T., et al. (2016). Cascading failure analysis and restoration strategy in an interdependent network. J. Phys. Math. Theor. **49**: 195101. https://doi.org/10.1088/1751-8113/49/19/195101.
117. Shi, Y., Zhai, G., Xu, L., et al. (2021). Assessment methods of urban system resilience: From the perspective of complex adaptive system theory. Cities **112**: 103141. https://doi.org/10.1016/j.cities.2021.103141.
118. Burby, R.J., Deyle, R.E., Godschalk, D.R., et al. (2000). Creating hazard resilient communities through land-use planning. Nat. Hazards Rev. **1**: 99–106. https://doi.org/10.1061/(asce)1527-6988(2000)1:2(99).
119. Du, M., Zhang, X., Wang, Y., et al. (2020). An operationalizing model for measuring urban resilience on land expansion. Habitat Int. **102**: 102206. https://doi.org/10.1016/j.habitatint.2020.102206.
120. Mallick, S.K. (2021). Prediction-adaptation-resilience (par) approach-a new pathway towards future resilience and sustainable development of urban landscape. Geogr. Sustain. **2**: 127–133. https://doi.org/10.1016/j.geosus.2021.06.002.
121. Zhao, L., Li, H., Sun, Y., et al. (2017). Planning emergency shelters for urban disaster resilience: An integrated location-allocation modeling approach. Sustainability **9**: 2098. https://doi.org/10.3390/su9112098.
122. Merilainen, E. (2020). The dual discourse of urban resilience: robust city and self-organised neighbourhoods. Disasters **44**: 125–151. https://doi.org/10.1111/disa.12367.
123. Liang, D., De Jong, M., Schraven, D., et al. (2022). Mapping key features and dimensions of the inclusive city: A systematic bibliometric analysis and literature study. Int. J. Sustain. Dev. World Ecol. **29**: 60–79. https://doi.org/10.1080/13504509.2021.1911873.
124. Turok, I., and Scheba, A. (2019). 'Right to the city'and the new urban agenda: learning from the right to housing. Territ. Politic. Gov. **7**: 494–510. https://doi.org/10.1080/21622671.2018.1499549.
125. Salahub, J.E., Gottsbacher, M., and De Boer, J. (2018). Social Theories of Urban Violence in the Global South (Routledge). https://doi.org/10.4324/9781351254724.
126. Delmelle, E., Nilsson, I., and Adu, P. (2021). Poverty suburbanization, job accessibility, and employment outcomes. Soc. Incl. **9**: 166–178. https://doi.org/10.17645/si.v9i2.3735.
127. Ghonimi, I. (2021). The role of urban space configuration in maintaining social inclusion: A comparison of four types of neighborhoods in greater cairo region-egypt. Can. J. Urban Res. **39**: 75–104. https://doi.org/10.21608/jur.2021.30232.1002.
128. Zhang, Y., Xu, F., Chen, L., et al. (2024). Counterfactual mobility network embedding reveals prevalent accessibility gaps in us cities. Humanit. Soc. Sci. Commun. **11**: 87. https://doi.org/10.1057/s41599-023-02570-5.
129. Beall, J. (2000). From the culture of poverty to inclusive cities: re-framing urban policy and politics. J. Int. Dev. **12**: 843–856. https://doi.org/10.1002/1099-1328(200008)12:6¸843::aid-jid713¿3.0.co;2-g.
130. Blumenstock, J., Cadamuro, G., and On, R. (2015). Predicting poverty and wealth from mobile phone metadata. Science **350**: 1073–1076. https://doi.org/10.1126/science.aac4420.
131. Tai, X.H., Mehra, S., and Blumenstock, J.E. (2022). Mobile phone data reveal the effects of violence on internal displacement in Afghanistan. Nat. Human Behav. **6**: 624–634. https://doi.org/10.1038/s41562-022-01336-4.
132. Maantay, J. (2002). Mapping environmental injustices: pitfalls and potential of geographic information systems in assessing environmental health and equity. Environ. Health Perspect. **110**: 161–171. https://doi.org/10.1289/ehp.02110s2161.
133. Sen, S., Hobson, J., and Joshi, P. (2003). The pune slum census: creating a socio-economic and spatial information base on a gis for integrated and inclusive city development. Habitat Int. **27**: 595–611. https://doi.org/10.1016/s0197-3975(03)00007-9.
134. Löfving, L., Kamuf, V., Heleniak, T., et al. (2022). Can digitalization be a tool to overcome spatial injustice in sparsely populated regions? the cases of digital västerbotten (sweden) and smart country side (germany). Eur. Plann. Stud. **30**: 917–934. https://doi.org/10.1080/09654313.2021.1928053.
135. Stehlin, J. (2014). Regulating inclusion: Spatial form, social process, and the normalization of cycling practice in the usa. Mobilities **9**: 21–41. https://doi.org/10.1080/17450101.2013.784527.
136. Souche, S., Mercier, A., and Ovtracht, N. (2016). The impacts of urban pricing on social and spatial inequalities: The case study of lyon (france). Urban Stud. **53**: 373–399. https://doi.org/10.1177/0042098014563484.
137. Gerometta, J., Haussermann, H., and Longo, G. (2005). Social innovation and civil society in urban governance: Strategies for an inclusive city. Urban Stud. **42**: 2007–2021. https://doi.org/10.1080/00420980500279851.
138. Muchadenyika, D. (2015). Slum upgrading and inclusive municipal governance in harare, zimbabwe: New perspectives for the urban poor. Habitat Int. **48**: 1–10. https://doi.org/10.1016/j.habitatint.2015.03.003.
139. Fredericks, J., Hespanhol, L., Parker, C., et al. (2018). Blending pop-up urbanism and participatory technologies: Challenges and opportunities for inclusive city making. City Cult. Soc **12**: 44–53. https://doi.org/10.1016/j.ccs.2017.06.005.
140. Un-Habitat (2012). Enhancing Urban Safety and Security: Global Report on Human Settlements 2007 (Routledge). https://doi.org/10.4324/9781849771146.
141. Andersson, C. (2014). Un-habitat's safer cities programme. Int. Perspect. Crime Prev. **6**: 89–93. https://doi.org/10.4324/9780429463426-5.
142. Cozens, P.M., Saville, G., and Hillier, D. (2005). Crime prevention through environmental design (cpted): a review and modern bibliography. Property Manag. **23**: 328–356. https://doi.org/10.1108/02637470510631483.
143. Dong, B., Egger, P.H., and Guo, Y. (2020). Is poverty the mother of crime? evidence from homicide rates in china. PLoS One **15**: e0233034. https://doi.org/10.1371/journal.pone.0233034.
144. Sampson, R.J., and Wilson, W.J. (2020). Toward a theory of race, crime, and urban inequality. In Crime, Inequality and the State (Routledge), pp. 312–325. https://doi.org/10.4324/9781003060581-24.
145. Piroozfar, P., Farr, E.R., Aboagye-Nimo, E., et al. (2019). Crime prevention in urban spaces through environmental design: A critical uk perspective. Cities **95**: 102411. https://doi.org/10.1016/j.cities.2019.102411.
146. Reatti, S. (2020). Active citizenship in urban security policies: Is neighborhood watch a solution? In Handbook of Research on Trends and Issues in Crime Prevention, Rehabilitation, and Victim Support (IGI Global), pp. 447–462. https://doi.org/10.4018/978-1-7998-1286-9.ch026.
147. Samanta, S., Sen, G., and Ghosh, S.K. (2022). A literature review on police patrolling problems. Ann. Oper. Res. **316**: 1063–1106. https://doi.org/10.1007/s10479-021-04167-0.
148. Mawby, R.I. (2023). Comparative Policing Issues: The British and American Experience in International Perspective (Taylor & Francis). https://doi.org/10.4324/9781003360452.
149. Tundis, A., Kaleem, H., and Mühlhäuser, M. (2020). Detecting and tracking criminals in the real world through an iot-based system. Sensors **20**: 3795. https://doi.org/10.3390/s20133795.
150. Piza, E.L., Welsh, B.C., Farrington, D.P., et al. (2019). Cctv surveillance for crime prevention: A 40-year systematic review with meta-analysis. Criminol. Publ. Pol. **18**: 135–159. https://doi.org/10.1111/1745-9133.12419.
151. Long, D., Liu, L., Xu, M., et al. (2021). Ambient population and surveillance cameras: The guardianship role in street robbers' crime location choice. Cities **115**: 103223. https://doi.org/10.1016/j.cities.2021.103223.
152. Brown-Luthango, M., Reyes, E., and Gubevu, M. (2017). Informal settlement upgrading and safety: experiences from cape town, south africa. J. Hous. Built Environ. **32**: 471–493. https://doi.org/10.1007/s10901-016-9523-4.
153. Matzopoulos, R., Bloch, K., Lloyd, S., et al. (2020). Urban upgrading and levels of interpersonal violence in cape town, south africa: The violence prevention through urban upgrading programme. Soc. Sci. Med. **255**: 112978. https://doi.org/10.1016/j.socscimed.2020.112978.
154. Catlett, C., Cesario, E., Talia, D., et al. (2019). Spatiotemporal crime predictions in smart cities: A data-driven approach and experiments. Pervasive Mob. Comput. **53**: 62–74. https://doi.org/10.1016/j.pmcj.2019.01.003.
155. Gill, C., Weisburd, D., Telep, C.W., et al. (2014). Community-oriented policing to reduce crime, disorder and fear and increase satisfaction and legitimacy among citizens: A systematic review. J. Exp. Criminol. **10**: 399–428. https://doi.org/10.1007/s11292-014-9210-y.
156. Pridmore, J., Mols, A., Wang, Y., et al. (2019). Keeping an eye on the neighbours: Police, citizens, and communication within mobile neighbourhood crime prevention groups. Police J. **92**: 97–120. https://doi.org/10.1177/0032258x18768397.

157. Alves, L.G., Ribeiro, H.V., and Rodrigues, F.A. (2018). Crime prediction through urban metrics and statistical learning. Physica A **505**: 435–443. https://doi.org/10.1016/j.physa.2018.03.084.
158. Feng, M., Zheng, J., Ren, J., et al. (2019). Big data analytics and mining for effective visualization and trends forecasting of crime data. IEEE Access **7**: 106111–106123. https://doi.org/10.1109/access.2019.2930410.
159. Huang, J., Boles, S.T., and Tarascon, J.-M. (2022). Sensing as the key to battery lifetime and sustainability. Nat. Sustain. **5**: 194–204. https://doi.org/10.1038/s41893-022-00859-y.
160. Chung, M.G., Frank, K.A., Pokhrel, Y., et al. (2021). Natural infrastructure in sustaining global urban freshwater ecosystem services. Nat. Sustain. **4**: 1068–1075. https://doi.org/10.1038/s41893-021-00786-4.
161. Silva, B.N., Khan, M., Jung, C., et al. (2018). Urban planning and smart city decision management empowered by real-time data processing using big data analytics. Sensors **18**: 2994. https://doi.org/10.3390/s18092994.
162. Liu, Z., Ciais, P., Deng, Z., et al. (2020). Carbon monitor, a near-real-time daily dataset of global co2 emission from fossil fuel and cement production. Sci. Data **7**: 392. https://doi.org/10.1038/s41597-020-00708-7.
163. Wang, J., and Lu, F. (2021). Modeling the electricity consumption by combining land use types and landscape patterns with nighttime light imagery. Energy **234**: 121305. https://doi.org/10.1016/j.energy.2021.121305.
164. Lehmann, M.K., Gurlin, D., Pahlevan, N., et al. (2023). Gloria-a globally representative hyperspectral *in situ* dataset for optical sensing of water quality. Sci. Data **10**: 100. https://doi.org/10.1016/j.rse.2021.112860.
165. Mena, J.B., and Malpica, J.A. (2005). An automatic method for road extraction in rural and semi-urban areas starting from high resolution satellite imagery. Pattern Recogn. Lett. **26**: 1201–1220. https://doi.org/10.1016/j.patrec.2004.11.005.
166. Zheng, Y., Capra, L., Wolfson, O., et al. (2014). Urban computing: concepts, methodologies, and applications. ACM Trans. Intell. Syst. Technol. **5**: 1–55. https://doi.org/10.1145/2629592.
167. Zheng, Y., Liu, F., and Hsieh, H.-P. (2013). U-air: When urban air quality inference meets big data. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1436–1444. https://doi.org/10.1145/2487575.2488188.
168. Wang, S., and Cao, J. (2021). AI and deep learning for urban computing. Urban. Inf. 815–844. https://doi.org/10.1007/978-981-15-8983-6_43.
169. Li, F., Feng, J., Yan, H., et al. (2023). Dynamic graph convolutional recurrent network for traffic prediction: Benchmark and solution. ACM Trans. Knowl. Discov. Data **17**: 1–21. https://doi.org/10.1145/3532611.
170. Espeholt, L., Agrawal, S., Sønderby, C., et al. (2022). Deep learning for twelve hour precipitation forecasts. Nat. Commun. **13**: 5145. https://doi.org/10.1038/s41467-022-32483-x.
171. Shao, Z., Wang, F., Xu, Y., et al. (2025). Exploring progress in multivariate time series forecasting: Comprehensive benchmarking and heterogeneity analysis. IEEE Trans. Knowl. Data Eng. **37**: 291–305. https://doi.org/10.1109/tkde.2024.3484454.
172. Yu, C., Wang, F., Shao, Z., et al. (2024). Ginar: An end-to-end multivariate time series forecasting model suitable for variable missing. In Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 3989–4000. https://doi.org/10.1145/3637528.3672055.
173. Li, G., Zhao, Z., Guo, X., et al. (2024). Towards integrated and fine-grained traffic forecasting: A spatiotemporal heterogeneous graph transformer approach. Inf. Fusion **102**: 102063. https://doi.org/10.1016/j.inffus.2023.102063.
174. Bi, S., Yuan, C., Liu, S., et al. (2022). Spatiotemporal prediction of urban online car-hailing travel demand based on transformer network. Sustainability **14**: 13568. https://doi.org/10.3390/su142013568.
175. Yu, C., Wang, F., Shao, Z., et al. (2023). Dsformer: A double sampling transformer for multivariate time series long-term prediction. In Proceedings of the 32nd ACM International Conference on Information and Knowledge Management, pp. 3062–3072. https://doi.org/10.1145/3583780.3614851.
176. Jiang, J., Han, C., Zhao, W.X., et al. (2023). Pdformer: Propagation delay-aware dynamic long-range transformer for traffic flow prediction. Proc. AAAI Conf. Artif. Intell. **37**: 4365–4373. https://doi.org/10.1609/aaai.v37i4.25556.
177. Day, A.K., and Radford, A.D. (1998). In Proceedings of the 3th Conference on Computer Aided Architectural Design Research in Asia, pp. 183–192. https://doi.org/10.52842/conf.caadria.1998.183.
178. Karnouskos, S., and De Holanda, T.N. (2009). Simulation of a smart grid city with software agents. In 2009 Third UKSim European Symposium on Computer Modeling and Simulation (IEEE), pp. 424–429. https://doi.org/10.1109/ems.2009.53.
179. Long, Q., Wang, H., Li, T., et al. (2023). Practical synthetic human trajectories generation based on variational point processes. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 4561–4571. https://doi.org/10.1145/3580305.3599888.
180. Yuan, Y., Ding, J., Wang, H., et al. (2022). Activity trajectory generation via modeling spatiotemporal dynamics. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 4752–4762. https://doi.org/10.1145/3534678.3542671.
181. Qian, T., Chen, Y., Cong, G., et al. (2024). Adaptraj: A multi-source domain generalization framework for multi-agent trajectory prediction. In 2024 IEEE 40th International Conference on Data Engineering (ICDE) (IEEE), pp. 5048–5060. https://doi.org/10.1109/icde60146.2024.00113.
182. Goodfellow, I., Pouget-Abadie, J., Mirza, M., et al. (2020). Generative adversarial networks. Commun. ACM **63**: 139–144. https://doi.org/10.1145/3422622.
183. Kingma, D.P., and Welling, M. (2014). Auto-encoding variational bayes. In International Conference on Learning Representations, pp. 1–14. https://doi.org/10.18653/v1/2020.coling-main.458.
184. Ho, J., and Ermon, S. (2016). Generative adversarial imitation learning. Adv. Neural Inf. Process. Syst. **29**. https://doi.org/10.5220/0011856700003467.
185. Ho, J., Jain, A., and Abbeel, P. (2020). Denoising diffusion probabilistic models. Adv. Neural Inf. Process. Syst. **33**: 6840–6851. https://doi.org/10.7551/mitpress/7503.003.0070.
186. Østergård, T., Jensen, R.L., and Maagaard, S.E. (2016). Building simulations supporting decision making in early design–a review. Renewable Sustainable Energy Rev. **61**: 187–201. https://doi.org/10.1016/j.rser.2016.03.045.
187. Kim, J.-H., and Yum, B.-J. (1993). A heuristic method for solving redundancy optimization problems in complex systems. IEEE Trans. Reliab. **42**: 572–578. https://doi.org/10.1109/24.273585.
188. Kaelbling, L.P., Littman, M.L., and Moore, A.W. (1996). Reinforcement learning: A survey. J. Artif. Intell. Res. **4**: 237–285. https://doi.org/10.1613/jair.301.
189. Hao, Q., Xu, F., Chen, L., et al. (2021). Hierarchical reinforcement learning for scarce medical resource allocation with imperfect information. In Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pp. 2955–2963. https://doi.org/10.1145/3447548.3467181.
190. Zhang, Z., Zhang, D., and Qiu, R.C. (2019). Deep reinforcement learning for power system applications: An overview. CSEE J. Power Energy Syst. **6**: 213–225. https://doi.org/10.17775/cseejpes.2019.00920.
191. Wei, H., Zheng, G., Yao, H., et al. (2018). Intellilight: A reinforcement learning approach for intelligent traffic light control. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 2496–2505. https://doi.org/10.1145/3219819.3220096.
192. Mudassir, G., and Di Marco, A. (2021). Social-based city reconstruction planning in case of natural disasters: a reinforcement learning approach. In 2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC) (IEEE), pp. 493–503. https://doi.org/10.1109/compsac51774.2021.00074.
193. Zheng, Y., Lin, Y., Zhao, L., et al. (2023). Spatial planning of urban communities via deep reinforcement learning. Nat. Comput. Sci. **3**: 748–762. https://doi.org/10.1038/s43588-023-00503-5.
194. Hussein, A., Gaber, M.M., Elyan, E., et al. (2017). Imitation learning: A survey of learning methods. ACM Comput. Surv. **50**: 1–35. https://doi.org/10.1145/3054912.
195. Zhang, J., Jin, D., and Li, Y. (2022). Mirage: an efficient and extensible city simulation framework (systems paper). In Proceedings of the 30th International Conference on Advances in Geographic Information Systems, pp. 1–4. https://doi.org/10.1145/3557915.3560950.
196. Zhang, J., Ao, W., Jin, D., et al. (2023). A city-level high-performance spatiotemporal mobility simulation system. In Proceedings of the 1st ACM SIGSPATIAL International Workshop on Sustainable Mobility, pp. 23–32. https://doi.org/10.1145/3615899.3627936.
197. Li, R., Wang, H., and Li, Y. (2023). Learning slow and fast system dynamics via automatic separation of time scales. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 4380–4390. https://doi.org/10.1145/3580305.3599858.
198. Wang, H., Yu, Q., Liu, Y., et al. (2021). Spatiotemporal urban knowledge graph enabled mobility prediction. In Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies, *5*, pp. 1–24. https://doi.org/10.1145/3494993.
199. Li, J., Wang, H., and Chen, X. (2024). Physics-informed neural ode for post-disaster mobility recovery. In Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 1587–1598. https://doi.org/10.1145/3637528.3672027.
200. Yuan, Y., Ding, J., Shao, C., et al. (2023). Spatiotemporal diffusion point processes. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 3173–3184. https://doi.org/10.1145/3580305.3599511.
201. Mao, J., Cao, L., Gao, C., et al. (2023). Detecting vulnerable nodes in urban infrastructure interdependent network. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 4617–4627. https://doi.org/10.1145/3580305.3599804.
202. Cavalcanti, T., Da, M.D., and Santos, M. (2019). On the determinants of slum formation. Econ. J. **129**: 1971–1991. https://doi.org/10.1111/ecoj.12626.
203. Mahabir, R., Crooks, A., Croitoru, A., et al. (2016). The study of slums as social and physical constructs: Challenges and emerging research opportunities. Reg. Stud. Reg. Sci. **3**: 399–419. https://doi.org/10.1080/21681376.2016.1229130.
204. Tzachor, A., Sabri, S., Richards, C.E., et al. (2022). Potential and limitations of digital twins to achieve the sustainable development goals. Nat. Sustain. **5**: 822–829. https://doi.org/10.1038/s41893-022-00923-7.
205. Batty, M. (2024). Digital twins in city planning. Nat. Comput. Sci. **4**: 192–199. https://doi.org/10.1038/s43588-024-00606-7.
206. Moroni, S., and Chiffi, D. (2022). Uncertainty and planning: cities, technologies and public decision-making. Perspect. Sci. **30**: 237–259. https://doi.org/10.1162/posc_a_00413.
207. Badmos, O.S., Rienow, A., Callo-Concha, D., et al. (2019). Simulating slum growth in lagos: An integration of rule based and empirical based model. Comput. Environ. Urban Syst. **77**: 101369. https://doi.org/10.1016/j.compenvurbsys.2019.101369.
208. Zheng, Y., Su, H., Ding, J., et al. (2023). Road planning for slums via deep reinforcement learning. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 5695–5706. https://doi.org/10.1145/3580305.3599901.
209. Agyemang, F.S.K., Silva, E., and Fox, S. (2022). Modelling and simulating 'informal urbanization': An integrated agent-based and cellular automata model of urban residential

growth in ghana. Environ. Plan. B Urban Anal. City Sci. ***50***: 863–877. https://doi.org/10.1177/23998083211068843.
210. Thomson, D.R., Stevens, F.R., Chen, R., et al. (2022). Improving the accuracy of gridded population estimates in cities and slums to monitor sdg 11: Evidence from a simulation study in namibia. Land Use Pol. ***123***: 106392. https://doi.org/10.1016/j.landusepol.2022.106392.
211. Brown, A.M. (2019). Planning for less planning: Supporting informal food systems in nairobi. In Routledge Handbook of Urban Planning in Africa (Routledge), pp. 354–365. https://doi.org/10.4324/9781351271844-24.
212. Ahmed, S.A.K.S., Ajisola, M., Azeem, K., et al. (2020). Impact of the societal response to covid-19 on access to healthcare for non-covid-19 health issues in slum communities of bangladesh, kenya, nigeria and pakistan: results of pre-covid and covid-19 lockdown stakeholder engagements. BMJ Glob. Health ***5***: e003042. https://doi.org/10.1136/bmjgh-2020-003042.
213. Badmos, O.S., Callo-Concha, D., Agbola, B., et al. (2020). Determinants of residential location choices by slum dwellers in Lagos megacity. Cities ***98***: 102589. https://doi.org/10.1016/j.cities.2019.102589.
214. Trindade, T.C., MacLean, H.L., and Posen, I.D. (2021). Slum infrastructure: Quantitative measures and scenarios for universal access to basic services in 2030. Cities ***110***: 103050. https://doi.org/10.1016/j.cities.2020.103050.
215. Tan, S., and Taeihagh, A. (2020). Smart city governance in developing countries: A systematic literature review. Sustainability ***12***: 899. https://doi.org/10.3390/su12030899.
216. Marques, E.C.L. (2024). Continuities and transformations in the studies of urban politics and governments. Nat. Cities ***1***: 22–29. https://doi.org/10.1038/s44284-023-00004-6.
217. Karvonen, A. (2020). Urban techno-politics: knowing, governing, and imagining the city. Sci. Cult. ***29***: 417–424. https://doi.org/10.1080/09505431.2020.1766011.
218. Zhang, J., Hua, X.-S., Huang, J., et al. (2019). City brain: practice of large-scale artificial intelligence in the real world. IET Smart Cities ***1***: 28–37. https://doi.org/10.1049/iet-smc.2019.0034.
219. Feng, L., Ying, L., and Yunqin, Z. (2021). Discussion on the definition and construction principles of city brain. In 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), pp. 1101–1105. https://doi.org/10.1109/ICBAIE52039.2021.9390064.
220. Caprotti, F., and Liu, D. (2022). Platform urbanism and the chinese smart city: the co-production and territorialisation of hangzhou city brain. Geojournal ***87***: 1559–1573. https://doi.org/10.1007/s10708-020-10320-2.
221. Chu, Z., Cheng, M., and Yu, N.N. (2021). A smart city is a less polluted city. Technol. Forecast. Soc. Change ***172***: 121037. https://doi.org/10.1016/j.techfore.2021.121037.
222. Wu, D., Xie, Y., and Lyu, S. (2023). Disentangling the complex impacts of urban digital transformation and environmental pollution: Evidence from smart city pilots in china. Sustain. Cities Soc. ***88***: 104266. https://doi.org/10.1016/j.scs.2022.104266.
223. Anagnostopoulos, T., Zaslavsky, A., Kolomvatsos, K., et al. (2017). Challenges and opportunities of waste management in iot-enabled smart cities: a survey. IEEE Trans. Sustain. Comput. ***2***: 275–289. https://doi.org/10.1109/tsusc.2017.2691049.
224. Molinillo, S., Anaya-Sánchez, R., Morrison, A.M., et al. (2019). Smart city communication via social media: Analysing residents' and visitors' engagement. Cities ***94***: 247–255. https://doi.org/10.1016/j.cities.2019.06.003.
225. Yao, F., and Wang, Y. (2020). Towards resilient and smart cities: A real-time urban analytical and geo-visual system for social media streaming data. Sustain. Cities Soc. ***63***: 102448. https://doi.org/10.1016/j.scs.2020.102448.
226. Hodorog, A., Petri, I., and Rezgui, Y. (2022). Machine learning and natural language processing of social media data for event detection in smart cities. Sustain. Cities Soc. ***85***: 104026. https://doi.org/10.1016/j.scs.2022.104026.
227. Cardullo, P., and Kitchin, R. (2019). Being a 'citizen'in the smart city: Up and down the scaffold of smart citizen participation in dublin, ireland. Geojournal ***84***: 1–13. https://doi.org/10.1007/s10708-018-9845-8.
228. Jang, S.-G., and Gim, T.H.T. (2022). Considerations for encouraging citizen participation by information-disadvantaged groups in smart cities. Sustain. Cities Soc. ***76***: 103437. https://doi.org/10.1016/j.scs.2021.103437.
229. Berntzen, L., and Johannessen, M.R. (2016). The Role of Citizen Participation in Municipal Smart City Projects: Lessons Learned from Norway. Smarter as the new urban agenda: A comprehensive view of the 21st century city: 299–314. https://doi.org/10.1007/978-3-319-17620-8_16.
230. Javed, A.R., Shahzad, F., Rehman, S.u., et al. (2022). Future smart cities requirements, emerging technologies, applications, challenges, and future aspects. Cities ***129***: 103794. https://doi.org/10.1016/j.cities.2022.103794.
231. Wu, Z., Pan, S., Long, G., et al. (2020). Connecting the dots: Multivariate time series forecasting with graph neural networks. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 753–763. https://doi.org/10.1145/3394486.3403118.
232. Shao, Z., Zhang, Z., Wang, F., et al. (2022). Pre-training enhanced spatial-temporal graph neural network for multivariate time series forecasting. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 1567–1577. https://doi.org/10.1145/3534678.3539396.
233. Cheng, S., Lu, F., Peng, P., et al. (2018). Short-term traffic forecasting: An adaptive st-knn model that considers spatial heterogeneity. Comput. Environ. Urban Syst. ***71***: 186–198. https://doi.org/10.1016/j.compenvurbsys.2018.05.009.
234. Cheng, S., Lu, F., Peng, P., et al. (2021). Short-term traffic forecasting by mining the non-stationarity of spatiotemporal patterns. IEEE Trans. Intell. Transport. Syst. ***22***: 6365–6383. https://doi.org/10.1109/tits.2020.2991781.
235. Yang, S., Wu, J., Du, Y., et al. (2017). Ensemble learning for short-term traffic prediction based on gradient boosting machine. J. Sens. ***2017***: 1–15. https://doi.org/10.1155/2017/7074143.
236. Chen, C., Wei, H., Xu, N., et al. (2020). Toward a thousand lights: Decentralized deep reinforcement learning for large-scale traffic signal control. Proc. AAAI Conf. Artif. Intell. ***34***: 3414–3421. https://doi.org/10.1609/aaai.v34i04.5744.
237. Qiu, W., Chen, H., and An, B. (2019). Dynamic electronic toll collection via multi-agent deep reinforcement learning with edge-based graph convolutional networks. IJCAI: 4568–4574. https://doi.org/10.24963/ijcai.2019/635.
238. Long, J., Gao, Z., Zhang, H., et al. (2010). A turning restriction design problem in urban road networks. Eur. J. Oper. Res. ***206***: 569–578. https://doi.org/10.1016/j.ejor.2010.03.013.
239. Zhang, H., Luo, M., Pei, T., et al. (2023). Unequal urban heat burdens impede climate justice and equity goals. Innovation ***4***: 100488. https://doi.org/10.1016/j.xinn.2023.100488.
240. Agreement, P. (2015). Paris agreement. In Report of the Conference of the Parties to the United Nations Framework Convention on Climate Change (21st Session, 2015: Paris), *4* (Retrived December), p. 2017. HeinOnline. https://doi.org/10.29171/acku_pamphlet_k3585_5_a47_2018_n1288_english_title1.
241. Chen, J.M. (2021). Carbon neutrality: Toward a sustainable future. Innovation ***2***: 100127. https://doi.org/10.1016/j.xinn.2021.100127.
242. Dasgupta, S., Lall, S., and Wheeler, D. (2022). Cutting Global Carbon Emissions: Where Do Cities Stand (World Bank Blogs). Published on Sustainable Cities. https://doi.org/10.1596/1813-9450-10224.
243. Seger, B., Robert, M., and Jiao, F. (2023). Best practices for electrochemical reduction of carbon dioxide. Nat. Sustain. ***6***: 236–238. https://doi.org/10.1038/s41893-022-01034-z.
244. Azizalrahman, H., and Hasyimi, V. (2019). A model for urban sector drivers of carbon emissions. Sustain. Cities Soc. ***44***: 46–55. https://doi.org/10.1016/j.scs.2018.09.035.
245. Song, X.-P., Huang, C., Saatchi, S.S., et al. (2015). Annual carbon emissions from deforestation in the amazon basin between 2000 and 2010. PLoS One ***10***: e0126754. https://doi.org/10.1371/journal.pone.0126754.
246. Friedlingstein, P., Jones, M.W., O'sullivan, M., et al. (2019). Global carbon budget 2019. Earth Syst. Sci. Data ***11***: 1783–1838. https://doi.org/10.5194/essd-11-1783-2019.
247. Eldering, A., Taylor, T.E., O'Dell, C.W., et al. (2019). The oco-3 mission: measurement objectives and expected performance based on 1 year of simulated data. Atmos. Meas. Tech. ***12***: 2341–2370. https://doi.org/10.5194/amt-12-2341-2019.
248. Ran, Y., and Li, X. (2019). Tansat: a new star in global carbon monitoring from china. Sci. Bull. ***64***: 284–285. https://doi.org/10.1016/j.scib.2019.01.019.
249. Ramaswami, A., Tong, K., Canadell, J.G., et al. (2021). Carbon analytics for net-zero emissions sustainable cities. Nat. Sustain. ***4***: 460–463. https://doi.org/10.1038/s41893-021-00715-5.
250. Oda, T., and Maksyutov, S. (2011). A very high-resolution (1 km $\times$1 km) global fossil fuel co 2 emission inventory derived using a point source database and satellite observations of nighttime lights. Atmos. Chem. Phys. ***11***: 543–556. https://doi.org/10.5194/acp-11-543-2011.
251. Dou, X., Wang, Y., Ciais, P., et al. (2022). Near-real-time global gridded daily co2 emissions. Innovation ***3***: 100182. https://doi.org/10.5194/egusphere-egu23-3303.
252. Zhu, R., Zhang, F., Yan, J., et al. (2023). A sustainable solar city: From utopia to reality facilitated by giscience. Innov. Geosci. ***1***: 100006. https://doi.org/10.59717/j.xinn-geo.2023.100006.
253. Bohm, M., Nanni, M., and Pappalardo, L. (2022). Gross polluters and vehicle emissions reduction. Nat. Sustain. ***5***: 699–707. https://doi.org/10.1038/s41893-022-00903-x.
254. Cheng, S., Lu, F., Peng, P., et al. (2021). Emission characteristics and control scenario analysis of vocs from heavy-duty diesel trucks. J. Environ. Manag. ***293***: 112915. https://doi.org/10.1016/j.jenvman.2021.112915.
255. Cheng, S., Zhang, B., Peng, P., et al. (2023). Health and economic benefits of heavy-duty diesel truck emission control policies in beijing. Environ. Int. ***179***: 108152. https://doi.org/10.1016/j.envint.2023.108152.
256. Nations U (2020). Goal 7: Ensure access to affordable, reliable, sustainable and modern energy for all. https://doi.org/10.1891/9780826190123.0018.
257. Mills, E. (2015). Can technology free developing countries from light poverty. Guardian ***30***. https://doi.org/10.47611/harp.128.
258. Bleischwitz, R., Spataru, C., VanDeveer, S.D., et al. (2018). Resource nexus perspectives towards the united nations sustainable development goals. Nat. Sustain. ***1***: 737–743. https://doi.org/10.1038/s41893-018-0173-2.
259. Asghar, N., Amjad, M.A., Rehman, H.u., et al. (2022). Achieving sustainable development resilience: Poverty reduction through affordable access to electricity in developing economies. J. Cleaner Prod. ***376***: 134040. https://doi.org/10.1016/j.jclepro.2022.134040.
260. Buldyrev, S.V., Parshani, R., Paul, G., et al. (2010). Catastrophic cascade of failures in interdependent networks. Nature ***464***: 1025–1028. https://doi.org/10.1038/nature08932.
261. Baetens, R., and Saelens, D. (2016). Modelling uncertainty in district energy simulations by stochastic residential occupant behaviour. J. Build. Perform. Simul. ***9***: 431–447. https://doi.org/10.1080/19401493.2015.1070203.
262. Haldane, V., De Foo, C., Abdalla, S.M., et al. (2021). Health systems resilience in managing the covid-19 pandemic: lessons from 28 countries. Nat. Med. ***27***: 964–980. https://doi.org/10.1038/s41591-021-01381-y.
263. Brunier, A., and Drysdale, C. (2020). Covid-19 Disrupting Mental Health Services in Most Countries, Who Survey (World Health Organization). https://doi.org/10.1037/e409862004-001.
264. Chan, H.F., Cheng, Z., Mendolia, S., et al. (2024). Residential mobility restrictions and adverse mental health outcomes during the covid-19 pandemic in the uk. Sci. Rep. ***14***: 1790. https://doi.org/10.1038/s41598-024-51854-6.

265. Baumgart, D.C. (2020). Digital advantage in the covid-19 response: perspective from canada's largest integrated digitalized healthcare system. NPJ Digit. Med. ***3***: 114. https://doi.org/10.1038/s41746-020-00326-y.
266. Rao, N.D., Kiesewetter, G., Min, J., et al. (2021). Household contributions to and impacts from air pollution in india. Nat. Sustain. ***4***: 859–867. https://doi.org/10.1038/s41893-021-00744-0.
267. Sun, H.Z., Zhao, J., Liu, X., et al. (2023). Antagonism between ambient ozone increase and urbanization-oriented population migration on chinese cardiopulmonary mortality. Innovation ***4***: 100517. https://doi.org/10.1016/j.xinn.2023.100517.
268. Pei, S., Yamana, T.K., Kandula, S., et al. (2021). Burden and characteristics of covid-19 in the united states during 2020. Nature ***598***: 338–341. https://doi.org/10.1038/s41586-021-03914-4.
269. Chen, L., Xu, F., Han, Z., et al. (2022). Strategic covid-19 vaccine distribution can simultaneously elevate social utility and equity. Nat. Human Behav. ***6***: 1503–1514. https://doi.org/10.1038/s41562-022-01429-0.
270. Olu, O. (2017). Resilient health system as conceptual framework for strengthening public health disaster risk management: an african viewpoint. Front. Public Health ***5***: 263. https://doi.org/10.3389/fpubh.2017.00263.
271. Moroni, S., De Franco, A., Pacchi, C., et al. (2023). Planning and meta-planning to cope with disruptive events: what can be learnt from the institutional response to the covid-19 pandemic in italy. City Territ. Archit. ***10***: 29. https://doi.org/10.1186/s40410-023-00216-2.
272. Chiappero-Martinetti, E., and Moroni, S. (2007). An analytical framework for conceptualizing poverty and re-examining the capability approach. J. Soc. Econ. ***36***: 360–375. https://doi.org/10.1016/j.socec.2006.12.002.
273. Adarov, A., Guénette, J.D., and Ohnsorge, F. (2022). Global income inequality and the covid-19 pandemic in three charts. J. Pol. Model. ***44***: 842–854. https://doi.org/10.1016/j.jpolmod.2022.09.013.
274. Shang, Y., Li, H., and Zhang, R. (2021). Effects of pandemic outbreak on economies: evidence from business history context. Front. Public Health ***9***: 632043. https://doi.org/10.3389/fpubh.2021.632043.
275. Pangallo, M., Aleta, A., del Rio-Chanona, R.M., et al. (2023). The unequal effects of the health–economy trade-off during the covid-19 pandemic. Nat. Human Behav. ***8***. https://doi.org/10.1038/s41562-023-01747-x.
276. Balland, P.-A., Jara-Figueroa, C., Petralia, S.G., et al. (2020). Complex economic activities concentrate in large cities. Nat. Human Behav. ***4***: 248–254. https://doi.org/10.1038/s41562-019-0803-3.
277. Florida, R. (2017). The new urban crisis: How our cities are increasing inequality, deepening segregation, and failing the middle class-and what we can do about it. Hachette UK. https://doi.org/10.5565/rev/dag.535.
278. Wang, K., Wang, C., and Chen, J. (2009). Analysis of the economic impact of different chinese climate policy options based on a cge model incorporating endogenous technological change. Energy Pol. ***37***: 2930–2940. https://doi.org/10.1016/j.enpol.2009.03.023.
279. Gao, J., Jun, B., Pentland, A.'., et al. (2021). Spillovers across industries and regions in china's regional economic diversification. Reg. Stud. ***55***: 1311–1326. https://doi.org/10.1080/00343404.2021.1883191.
280. Alshamsi, A., Pinheiro, F.L., and Hidalgo, C.A. (2018). Optimal diversification strategies in the networks of related products and of related research areas. Nat. Commun. ***9***: 1328. https://doi.org/10.1038/s41467-018-03740-9.
281. Liu, Y., Du, J., Wang, Y., et al. (2024). Overlooked uneven progress across sustainable development goals at the global scale: Challenges and opportunities. Innovation ***5***: 100573. https://doi.org/10.1016/j.xinn.2024.100573.
282. Jean, N., Burke, M., Xie, M., et al. (2016). Combining satellite imagery and machine learning to predict poverty. Science ***353***: 790–794. https://doi.org/10.1126/science.aaf7894.
283. Taylor, N. (2002). State surveillance and the right to privacy. Surveill. Soc. ***1***: 66–85. https://doi.org/10.24908/ss.v1i1.3394.
284. Yuan, Y., Shao, C., Ding, J., et al. (2024). Spatiotemporal few-shot learning via diffusive neural network generation. In The Twelfth International Conference on Learning Representations. https://doi.org/10.1109/nnice61279.2024.10498780.
285. Liang, W., Tadesse, G.A., Ho, D., et al. (2022). Advances, challenges and opportunities in creating data for trustworthy ai. Nat. Mach. Intell. ***4***: 669–677. https://doi.org/10.1038/s42256-022-00516-1.
286. Goodchild, M.F., and Li, W. (2021). Replication across space and time must be weak in the social and environmental sciences. Proc. Natl. Acad. Sci. USA ***118***: e2015759118. https://doi.org/10.1073/pnas.2015759118.
287. Luo, L., Wang, X., and Guo, H. (2022). Contribution of unesco designated sites to the achievement of sustainable development goals. Innovation ***3***: 100227. https://doi.org/10.1016/j.xinn.2022.100227.
288. Wang, K., Li, A., and Qu, X. (2023). Urban aerial mobility: Network structure, transportation benefits, and sino-us comparison. Innovation ***4***: 100393. https://doi.org/10.1016/j.xinn.2023.100393.
289. Wei, J., Tay, Y., Bommasani, R., et al. (2022). Emergent abilities of large language models. Trans. Mach. Learn. Res. https://doi.org/10.18653/v1/2021.emnlp-main.465.
290. Gao, C., Lan, X., Li, N., et al. (2024). Large language models empowered agent-based modeling and simulation: A survey and perspectives. Humanit. Soc. Sci. Commun. ***11***: 1259–1324. https://doi.org/10.1057/s41599-024-03611-3.

ACKNOWLEDGMENTS

This work was supported by National Natural Science Foundation of China (U23B2030, 62302261) and the National Key Research and Development Program of China (23IAA02114). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

Y. Li, T.Z., and F.W. formulated the initial concept. Y.Z., Y. Lin, and G.Z. reviewed the literature, wrote the draft, and created the figures. All authors contributed to and approved the manuscript.

DECLARATION OF INTERESTS

Y.X. and H.G. are Editorial Board members of *The Innovation* and were blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of these members and their research group.

LEAD CONTACT WEBSITE

https://fi.ee.tsinghua.edu.cn/.