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PERSPECTIVES

# Urgency and importance of local-scale modeling tools to support climate adaptation and sustainable development

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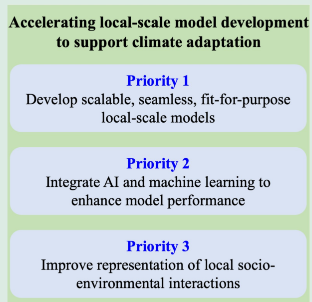
## HIGHLIGHTS

- The significance of local-scale models to support climate adaptation is highlighted.
- The challenges of developing local-scale models are explored.
- Recommendations for developing local-scale models are discussed.




**ABSTRACT:** Climate change presents a critical global challenge, threatening human well-being, ecosystems, economies, and societies. While mitigation efforts remain essential and critically important, the growing urgency of climate impacts necessitates immediate and effective adaptation measures. Effective adaptation strategies require advanced modeling tools with higher resolution, integration of ecosystem and social dynamics, and the ability to assess diverse adaptation scenarios. Local-scale models, which are performed at the scale of an administrative region, a country, or a specified region, are particularly valuable as they can incorporate specific adaptation measures and generate precise, context-specific insights. These models play a key role in formulating tailored climate adaptation strategies and action plans. This paper explores the significance and challenges in developing such models, emphasizing the pressing need to accelerate their advancement. We call on the scientific community and policymakers to prioritize the development of tailored local-scale modeling tools and services to enhance resilience and better support adaptive responses to the complex and evolving challenges posed by climate change and rapid urbanization at the local level.

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**KEYWORDS:** Climate adaptation, Local-scale model, Model development, Policy-making

## 1 Introduction

Climate change is one of the most pressing challenges of the 21st century, with far-reaching consequences for natural and socio-economic systems, public health, and human livelihoods worldwide. Beyond the overall rise in global temperatures, climate change is driving an increase in the frequency and intensity of extreme weather events, including heatwaves, heavy rainfall, severe storms, floods, and droughts, along with secondary impacts such as wildfires, sand and dust storms, and environmental degradation (IPCC, 2021). According to the 2024 World Economic Forum Risk Report, extreme weather events rank as the second most severe global risk in the short term (two years) and the highest global risk over the long term (ten years) (WEF, 2024). The consequences of these events are profound, causing substantial economic losses, damage to infrastructure, and threats to human well-being. Climate change affects multiple facets of our environment, including planetary health (encompassing marine and freshwater systems, biodiversity, and terrestrial ecosystems) and human society (impacting energy, water resources, food security, habitats, infrastructure, transportation, shipping, health, tourism, well-being, culture, and population migration). Addressing the complex, cascading, and systemic risks posed by human-induced climate change is an urgent priority, requiring coordinated global efforts and innovative solutions to protect both the planet and its inhabitants.

The fight against climate change has led to a global consensus, reflected in the establishment of international frameworks such as the Intergovernmental Panel on Climate Change (IPCC), the United Nations Framework Convention on Climate Change (UNFCCC), and the annual Conference of the Parties (COP) meetings, as well as a network of international climate governance initiatives. The Paris Agreement marked a milestone in global climate cooperation, with countries committing to ambitious mitigation goals aimed at reducing greenhouse gas emissions and limiting global temperature rise to within 1.5 or 2 °C. However, for the year 2024, the global average temperature had already reached about 1.55°C above pre-industrial levels, setting a new record (WMO, 2025). While mitigation remains a long-term process, it alone cannot address the immediate and escalating threats posed by climate change. As global warming intensifies, the increasing frequency and severity of extreme weather events underscore the need for climate adaptation—an essential and direct approach to reducing climate risks and protecting communities and ecosystems (Biesbroek and Lesnikowski, 2018; Zhang et al., 2022; Ouyang et al., 2023).

Although climate change is a global phenomenon, its impacts and associated risks vary significantly across regions, countries, and cities. Effective adaptation strategies and action plans require decision-makers to have access to detailed, localized information—not only about how climate change will affect specific areas but also about which local measures are most effective in adapting to its impacts. While global climate models are crucial for understanding large-scale climate patterns and trends, they lack the resolution necessary to capture localized variations, often overlooking critical details that influence climate impacts at regional and urban scales (Gutowski et al., 2020). As a result, significant efforts have been made globally to advance our understanding of regional climates through the development of regional climate models. Notable examples include the Regional Climate Model (RegCM) developed by the International Center for Theoretical Physics (ICTP), Italy; the Weather Research and Forecasting Model (WRF), the Regional Spectrum Model (RSM), the Regional Atmospheric Modeling System (RAMS), and the Pacific Northwest National Laboratory Regional Climate Model (PNNL-RCM) from the USA; the Providing Regional Climates for Impacts Studies (PRECIS) and the Hadley Centre Regional Model (HadRM) from the UK; the REgional Model (REMO) and the Climate version of the Consortium for Small-scale Modeling (CCLM) from Germany; the Rossby Centre regional climate model (RCA) from Sweden; and the Regional Integrated Environment Modeling System (RIEMS) and the Flexible Regional Ocean-Atmosphere-Land System model (FROALS) from China. Nevertheless, traditional climate models were primarily developed for predicting climate change rather than for assessing different adaptation mechanisms and evaluating their effectiveness. This limitation reduces their usefulness in providing actionable information for local policy-makers. The need for tailored climate adaptation strategies highlights the urgency of developing high-resolution, local-scale modeling tools capable of delivering more precise simulations of climate conditions at regional and urban levels. Such tailored models will support scientists and policymakers in assessing localized climate impacts—such as through risk mapping—across diverse sectors including ecosystems, agriculture, water resources, urban infrastructure, and human settlements, which are essential factors for identifying vulnerabilities and designing targeted adaptation strategies. Ideally, an integrated local-scale modeling framework could facilitate the incorporation of these differentiated sector-specific components to enable multi-risk assessments and support more context-sensitive adaptation planning.

The local-scale modeling indicates that the model is performed at the scale of an administrative region, a country, or a specified region, and the results can be more useful for policymakers on climate change adaptation and mitigation. The effectiveness of local-scale climate models for adaptation depends on several critical factors (Fig. 1). These models must go beyond simple downscaling of global climate projections. Ensuring consistency between scales and capturing two-way interactions between global and local climate dynamics is of paramount importance. Additionally, local-scale models must integrate fine-scale geographical details such as topography, land use, and urban characteristics, all of which significantly influence local climate conditions. Socioeconomic factors, including demographic patterns, infrastructure, and spatial vulnerabilities, must also be incorporated to enhance the model's applicability. Moreover, it is essential to account for regional differences in the relationship between extreme weather events and health outcomes—as well as other determinants of population resilience such as age distribution, health care access, and urban health exposure—to enhance the relevance and accuracy of climate-related health impact projections and the corresponding planning at finer spatial scale (Liu et al., 2023; Song et al., 2024). The interplay between air quality and climate is another key aspect that must be integrated into these models. Achieving this level of detail requires extensive observational data with high spatial and temporal resolution, presenting significant challenges for model development.

This paper provides an overview of the key challenges in developing local-scale climate adaptation models and offers recommendations to enhance their effectiveness in supporting adaptation strategies. While not exhaustive, we focus on critical issues that require further advancement in climate and environmental modeling to support climate adaptation, including:

**Data availability and model resolution**: Ensuring that observations and climate models meet fit-for-purpose requirements. **Multi-scale interactions and consistency**: Addressing boundary conditions and integrating one-atmosphere modeling approaches. **Seamless integrated modeling**: Incorporating interconnected Earth system elements and processes. **Model parameterization and calibration**: Improving the accuracy and applicability of local-scale models. **Human and societal factors**: Integrating externality cost functions and impact-based assessments. **Coupling meteorology and atmospheric composition models**: Exploring the co-benefits for climate and air quality. **Linking models with real-world applications**: Enhancing the practical implementation of adaptation strategies. **Understanding interaction chains and cascading effects**: Developing interdisciplinary models to support digital twins. **Multi-hazard early warning systems and long-term adaptation planning**: Streng-

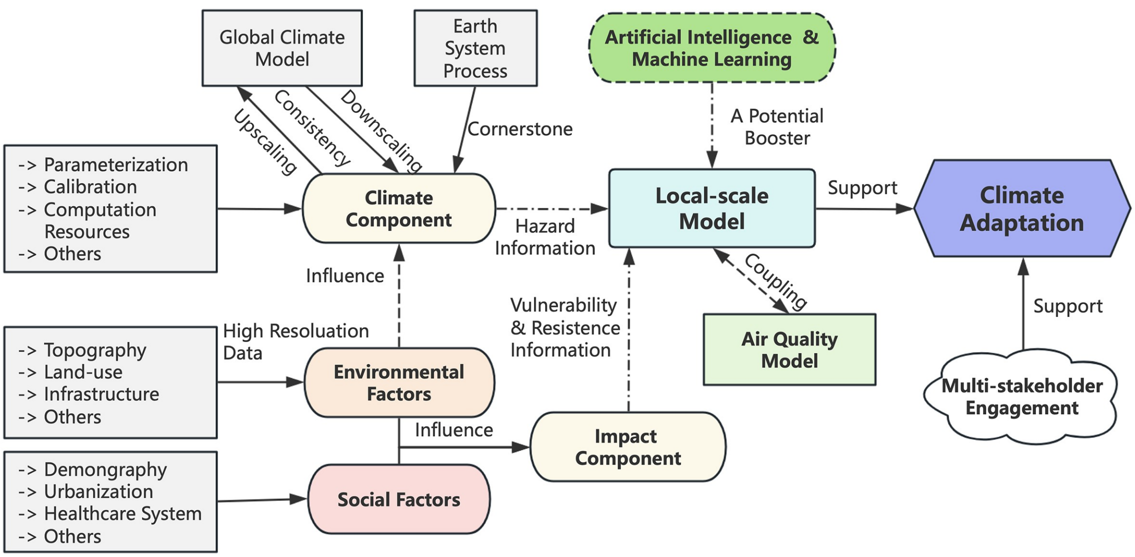


**Fig. 1** Schematic illustration for the development of local-scale modeling tools to support climate adaptation.

thening resilience at multiple scales. **Urban climate adaptation**: Advancing climate-smart, sustainable, and resilient cities.

By addressing these aspects, this paper aims to contribute to the ongoing efforts toward developing high-resolution, context-specific modeling tools that can effectively inform climate adaptation policies and strategies at the local level.

# 2 Challenges and recommendations for supporting local-scale model development

## 2.1 Data availability and resolution

Obtaining high-resolution observational data for various parameters remains a significant challenge. From local topography and detailed land-use information to demographic and infrastructure data, the need for accurate, granular datasets are fundamental for developing reliable local-scale models. However, such detailed datasets are often scarce, particularly in less-developed regions, making it difficult to construct precise and effective climate adaptation models. Emerging technologies, particularly satellite remote sensing technologies, offer a powerful means to address these data gaps. With their ability to provide consistent, high-resolution, and near-real-time observations across broad spatial scales, satellites can supplement ground-based measurements. The integration of these datasets—often aided by machine learning or data assimilation techniques—can significantly enhance spatial coverage and resolution, particularly in under-monitored regions.

This challenge further underscores the importance of capacity building in monitoring and data collection efforts (Creutzig et al., 2019). One notable example of large-scale data collection for climate adaptation is China’s National Census on Natural Disaster Risks, which systematically gathered critical information to support climate resilience efforts (SC, 2023). This initiative serves as a model for other countries to follow. To enhance the localization of climate models, we advocate for the seamless integration of digital, standardized, high-resolution, and comprehensive datasets derived from both ground-based and satellite sources. Bridging data gaps requires not only technological investment but also collaborative, cross-sectoral partnerships. A promising approach to bridging these gaps is the fusion of observational data with modeling efforts, as demonstrated by the World Urban Database and Access Portal Tools (WUDAPT) initiative. WUDAPT offers a low-cost, standardized framework for mapping Local Climate Zones (LCZs) using freely available satellite imagery and open-source tools, which supports generating urban canopy parameters to support multi-scale urban weather, climate, and environmental modeling (Ching et al., 2018, 2019). Additionally, Demuzere et al. (2021, 2022) suggested a web-based generator to create LCZ maps and built a global LCZ map. These coherent and consistent descriptions and information on form and function of urban morphology can significantly improve localized assessments, especially for data-scarce cities in developing countries. The concept of LCZ (Stewart and Oke, 2012), which describes the local climatic impacts of variation in the urban landscape, can be useful for climate-resilient urban planning and design modelling. However, it needs to be further advanced and implemented to comprehensively characterize urban climate and its derived impacts across time, space and depth. It is also important to integrate future climate scenario data with the LCZ framework to identify key priorities for urban climate adaptation (Mills et al., 2024; Yang et al., 2025).

Model resolution is another fundamental consideration and a critical factor in developing local-scale climate adaptation models, as it directly influences the accuracy and applicability of projected impacts. The appropriate spatial and temporal resolutions vary depending on the specific task and should follow a fit-for-purpose principle (Dee et al., 2024). In particular, the process of downscaling outputs from Global Circulation Models (GCMs) to finer resolutions—through either dynamical or statistical methods—is a crucial and active area of research, especially for regions where high-resolution observational data are limited. A comparison of different types of local-scale climate models is listed in Table 1. While this study does not focus on downscaling techniques per se, we emphasize the importance of ensuring that any model used for local adaptation planning operates at a resolution appropriate to both the scale of decision-making and the sensitivity of the relevant sector. Future work should further integrate advanced downscaling approaches to enhance the utility of climate projections for site-specific adaptation planning.

## 2.2 Multi-scale modeling, boundary conditions, and consistency

Downscaling global climate models to regional and local scales enables the simulation of global climate

**Table 1** Comparison of different types of local-scale climate models

| Model name/type | Description | Advantages | Disadvantages | Best uses | Key references |
|---|---|---|---|---|---|
| Dynamical Downscaling (e.g., WRF, RegCM, Enviro-HIRLAM) | Uses Regional Climate Models (RCMs) to dynamically downscale Global Climate Model (GCM) output. | - High spatial and temporal resolution<br>- Physically consistent<br>- Captures complex topography and coastlines | - Computationally expensive<br>- Needs high-quality input data<br>- Long run times | Urban planning, hydrological studies, regional risk assessments | Giorgi and Mearns (1999); Skamarock et al. (2008); Baklanov et al. (2017a); Wang et al. (2021) |
| Statistical Downscaling (e.g., SDSM, LARS-WG) | Uses empirical relationships between large-scale climate and local weather | - Low computational cost<br>- Easy to implement<br>- Can be applied at specific locations | - Limited in capturing non-stationary relationships<br>- Sensitive to quality and length of observational data | Agriculture planning, water resources, vulnerability mapping | Semenov and Barrow (1997); Wilby et al. (2002); Dafouf et al. (2025) |
| Empirical-Statistical Downscaling (e.g., BCSD, Delta Method) | Combines observed data and climate projections using statistical techniques | - Simplified method for scenario development<br>- Good for stakeholder communication<br>- Suitable for regions with limited data | - Simplifies physical processes<br>- Assumes stationarity of climate relationships | Risk communication, impact assessments, adaptation strategy design | Wood et al. (2004); Hay et al. (2000); Michalek et al. (2024) |
| Hybrid Models (e.g., LOCA, BCCAQ) | Combine dynamical and statistical approaches to leverage strengths of both | - Balances accuracy and efficiency<br>- Improved bias correction<br>- Better spatial representation | - Still computationally intensive<br>- Complex methodology<br>- Requires both high-quality obs. and GCM data | Coastal zone management, infrastructure planning, energy systems | Pierce et al. (2013); Werner and Cannon (2016); Lopez-Gomez et al. (2025) |
| High-Resolution Regional Climate Projections (e.g., UKCP Local, CORDEX) | Outputs from coordinated initiatives providing downscaled datasets | - Readily accessible<br>- Broadly validated<br>- Includes uncertainty quantification | - Limited flexibility for custom applications<br>- May not resolve local microclimates | National adaptation plans, ecosystem impact studies | Murphy et al. (2018); Giorgi et al. (2009); Langendijk et al. (2024) |
| Machine Learning Models (e.g., Random Forests, Neural Networks) | Data-driven models trained on observed and projected data | - Handles non-linear relationships<br>- Fast predictions<br>- Good for large datasets | - Black box behavior<br>- Requires large, clean datasets<br>- May not generalize well | Decision support tools, forecasting, socio-climate vulnerability | Reichstein et al. (2019); Ganguly et al. (2014); Hobeichi et al. (2023) |

impacts and large-scale phenomena at finer spatial resolutions (e.g., Fowler et al., 2007; Yoshikane and Yoshimura, 2023). However, most multi-scale modeling systems rely on one-way nesting, in other words, they do not effectively account for the feedback or upscaling of local-scale phenomena to larger scales. This limitation presents a significant research gap, as local-scale mitigation and adaptation measures can have broader implications that should be incorporated into global and regional modeling frameworks. Addressing this gap is essential to improve the accuracy and effectiveness of climate adaptation and mitigation strategies.

Coupling local-scale models with global climate models requires careful handling of lateral boundary conditions to ensure consistency across scales. However, achieving such consistency is often complex and challenging, as mismatches in boundary conditions can lead to inaccuracies in simulations. This challenge underscores the need for stronger collaboration among local-scale, regional, and global climate modeling communities.

A promising development in this area is the “One Atmosphere” approach, which aims to create next-generation multi-scale climate and Earth system models capable of resolving boundary condition issues and enabling two-way scale interactions. These models are currently under active development in the United States—most notably within the NCAR MUSICA/MPAS (Pfister et al., 2020) and CEMS3/SIMA (Danabasoglu et al., 2020) systems—and in Europe, with the ICON system (Jungclaus et al., 2022). These models utilize non-regular grids (e.g., Voronoi or hexagonal meshes), allowing operating at the global scale while concentrating high-resolution grids over specific focus areas, such as cities. However, despite these advancements, urbanization effects and micro-scale process parameterizations have yet to be fully implemented in such models. This limitation currently restricts their applicability for urban climate and adaptation modeling studies.

To advance this field, it is essential to support targeted research and model development efforts that address the aforementioned issues. In addition, workshops, training programs, and collaborative research initiatives should be further promoted, to foster knowledge exchange and the development of best practices to overcome these challenges.

## 2.3 Interconnected earth system processes

The interactions among various components of the

Earth system—including the atmosphere, oceans, and land surface—contribute to the complexities of local-scale modeling. The Earth system is dynamic, with its elements intricately interconnected. Changes in one component can trigger cascading effects on others, making it essential to capture these dynamic interactions when developing accurate models. For instance, understanding the nuanced relationship between upper-ocean temperatures and atmospheric circulation is vital for reducing uncertainties at the local scale (Xie et al., 2015).

The new generation of models leverages the seamless Earth System Modeling (ESM) approach, transitioning from isolated model components to integrated frameworks. This integration addresses emerging challenges in weather, climate, and atmospheric composition, which increasingly overlap in their interests, applications, and associated challenges. The seamless approach encompasses several dimensions of coupling, including temporal and spatial scales; physical, chemical, biological, and social processes; Earth system components; observation-model fusion techniques; data assimilation, validation, and verification; and links to social impacts, services, and end-users (Baklanov and Zhang, 2020). The World Meteorological Organization (WMO) research strategy outlines diverse methodologies and research needs for realizing seamless Earth System predictions (WMO, 2015). Notably, the Pan-Eurasian Experiment (PEEX) multidisciplinary program is developing a hierarchical framework of modern multi-scale models integrated with observational systems to address different elements of the Earth system (Kulmala et al., 2015; Mahura et al., 2024).

Advancing our understanding of local-scale interactions within the Earth system is a continuous and collaborative endeavor. Progress in this area depends on ongoing research, cross-disciplinary collaboration, technological innovation, and international cooperation, all of which are crucial for addressing the complexities of local-scale modeling and improving our capacity to predict localized climate variations with a greater accuracy.

### 2.4 Model parameterization and calibration

Local-scale models, with their ability to operate at finer spatial resolutions, excel in simulating fine-scale atmospheric phenomena such as storms and hurricanes. This capability is crucial for improving precipitation forecasts, predicting extreme weather events, and assessing the potential impacts of climate change at the local level. The parameterization of physical processes in local-scale models—including convection, cloud formation, and precipitation—requires continuous refinement and calibration. Rigorous validation and benchmarking against observational data are essential to ensure that these refined parameterizations accurately capture the targeted atmospheric phenomena.

While finer spatial resolution may improve simulations for specific regions or areas, achieving an optimal balance between model complexity and computational efficiency remains a persistent challenge—particularly for integrated models that aim to capture interactions across climate, environment, and health risks. These trade-offs must be carefully considered when developing models intended for application across multiple spatial scales. The choice of model complexity, resolution, and corresponding computational cost should be appropriate for the intended purpose. For example, the MEGAPOLI project proposed a hierarchy of urban canopy schemes tailored to different types and scales of models (MEGAPOLI, 2010; WMO, 2023a). Although local-scale models exist and are well established in certain domains, such as hydrology or groundwater modeling, there remains a lack of efficient, scalable, multi-sectoral integrated modeling frameworks that are accessible and applicable in resource-constrained settings. To better support climate adaptation and sustainable development, these models should be enhanced by integrating downscaling techniques that effectively utilize projections from global climate models, as well as upscaling approaches to assess the broader impacts of local-scale phenomena and adaptation measures. Such integration is critical to ensure consistency across spatial scales and to generate high-resolution, context-specific information that supports locally relevant adaptation decisions. We therefore call for increased efforts to develop and disseminate such integrated modeling tools to support climate-resilient planning across diverse regions.

Smarter parameterization and tuning techniques, which enable more efficient optimization, are key to addressing the trade-off between model complexity and computational efficiency. This involves identifying critical parameters and optimizing their values through approaches such as Bayesian optimization, Markov Chain Monte Carlo (MCMC), multiple very fast simulated annealing (MVFSA), and simulated stochastic approximation annealing (SSAA). However, it generally requires substantial computational resources and expertise. The integration of artificial intelligence (AI) and machine learning has the potential to be a game changer. Owing to its ability to learn and discover high-resolution relationships from observation or simulation data, AI technologies have already demonstrated significant advantages in various fields, including convective parameterization in climate models (Gentine et al., 2018; Yuval and O'Gorman, 2020) and weather forecasting models (Bi et al., 2023; Lam et al., 2023; Yoshikane and Yoshimura, 2023). Yet it must be noted that AI is not a panacea. While AI excels at uncovering relationships within data, the derived patterns are highly dependent on the quality, coverage and representativeness of training data, which might lead to systemic biases or overfitting. Additionally, due to the inherent 'black box' nature of AI, interpretability and alignment with physical principles remain significant challenges. In response, emerging approaches such as physics-informed machine learning (Karniadakis et al., 2021) and hybrid AI-physical modeling frameworks (Huang et al., 2024) are gaining increasing attention for their potential to improve robustness, trustworthiness, and scientific validity.

Incorporating AI into local-scale climate models holds tremendous promise due to its ability to efficiently leverage existing data and improve model performance. While developing AI-driven models typically requires substantial data and computational resources, once trained, these models can be shared and deployed in less-developed countries facing challenges such as limited observational capacity and constrained computing resources. This facilitates broader accessibility and application of advanced climate modeling techniques, supporting more effective adaptation strategies globally. The adoption of AI-driven modeling provides opportunities for capacity building and knowledge transfer. Although the application and interpretation of AI technologies require technical expertise, collaboration with international research institutions and targeted training programs can help develop these capabilities over time. Such efforts enable less-developed countries to gradually build the necessary expertise, leverage global advancements, and promote more inclusive participation in climate modeling and adaptation planning.

### 2.5 Human and societal factors

In local climate modeling, mitigation, and adaptation efforts, it is essential to move beyond predicting purely physical and meteorological variables (such as temperature, humidity, and wind velocity) toward impact-based predictions that evaluate climate change effects and the effectiveness of adaptation measures across various domains, including public health, social structures, and economic sectors. Implementing this approach requires expanding climate models to incorporate impact assessment, disaster risk reduction, and economic cost-benefit analysis modules (Mahura et al., 2024; Potter et al., 2025).

Integrating human and societal factors into local-scale models enhances the comprehensiveness and accuracy of climate projections while supporting optimized adaptation strategies. Demographic shifts, urbanization, and land-use practices not only influence climate patterns but are also affected by them, shaping the overall vulnerability of communities. Certain groups, such as marginalized populations, the elderly, and individuals with limited resources, are often disproportionately impacted by climate change. By incorporating demographic data and vulnerability assessments into models, targeted strategies can be developed to address the specific needs of these at-risk groups.

The resilience of populations to climate change varies considerably due to factors such as infrastructure quality, urban planning, healthcare systems, and cultural considerations. Customizing local models to reflect these specificities ensures that adaptation and mitigation strategies are contextually relevant and effective. Achieving this requires stronger collaboration between scientists and sociologists to develop a holistic understanding of the interplay among human behavior, social dynamics, and the physical environment.

### 2.6 Coupling with air quality models

For most developing countries, particularly in Asia, air pollution presents a significant additional threat to public health alongside climate change (Ouyang et al., 2022b). The coexistence of these challenges highlights the urgency of integrating climate mitigation and adaptation strategies with air quality management to achieve co-benefits (Ouyang et al., 2022a). Moreover, the interplay between air quality and climate change at local scales is complex, involving overlapping and interacting physical, chemical, and meteorological processes (Alapaty et al., 2012; Baklanov et al., 2017b).

Effectively coupling local-scale climate models with air quality models is essential for supporting local policy-making, optimizing resource allocation, and maximizing the benefits of environmental governance—particularly in resource-constrained regions. Achieving this requires a deeper understanding of the interactions between atmospheric composition and climate change, including their feedback mechanisms. Stronger collaboration between local climate and air quality modeling communities is crucial for advancing this integration.

To enhance understanding of these complex interactions between atmospheric chemistry and climate, it is recommended to promote the use of advanced simulation and forecasting models that account for chemical weather and chemical climate. Unlike traditional geochemical models, these models are specifically designed to simulate the formation, transformation and transport of chemical species in the atmosphere under varying meteorological conditions, enabling more accurate predictions of atmospheric composition and air pollution levels. Additionally, continued advancements in chemical weather and chemical climate modeling are necessary to develop effective emission reduction strategies that simultaneously contribute to both climate change mitigation and air quality improvement.

### 2.7 Linking models to real-world applications

Engaging local communities and involving stakeholders in the development, refinement, and implementation of local-scale climate models is crucial for ensuring that these models effectively address the specific needs of each region. Such collaborative efforts can improve model accuracy, build stakeholder trust, and foster a shared sense of responsibility in addressing climate challenges. Establishing a continuous dialogue and feedback loop between model developers and end-users should be prioritized to bridge the gap between scientific research and real-world applications. Multi-scale modeling tools and observation systems should serve as methodological and informational platforms for climate services at regional, national, and city levels. These platforms can support the analysis and development of optimal adaptation strategies for climate change (WMO, 2018; Koldunov and Jung, 2024). Effective climate services should incorporate at least two key adaptation strategy streams: early warning systems and long-term disaster risk reduction planning (Tang et al., 2021).

While most developments and applications of modern models and tools for climate adaptation have been driven by nationally or internationally led projects —largely dominated by Europe and the USA—developing countries are increasingly seeking active involvement in tailoring and applying such tools to meet their specific regional needs. For example, Estrada et al. (2022) developed a new AIRCC-Clim tool—a standalone, user-friendly software—for generating probabilistic regional climate change scenarios and risk measures for Mexico. Similarly, Tamayo et al. (2022) integrated multiple downscaled climate projections based on various methods to estimate uncertainties and provided a web viewer for accessing climate change scenarios for Latin America. Delgado et al. (2014) within the WISDOM collaborative project focusing on water-related information systems, realized the integration of climate modeling with water resource management in Vietnam, highlighting the importance of context-specific applications in different regions.

### 2.8 A special focus on urban areas for climate- and environment- smart cities

Urban areas, with their high population densities, extensive infrastructure, and economic activity, face heightened risks from climate change impacts such as extreme weather events, heatwaves, and air pollution. These vulnerabilities make cities a priority for deploying advanced climate modeling tools to support adaptation and mitigation efforts.

Existing approaches—such as Integrated Urban Services (IUS) (Baklanov et al., 2018, 2020; WMO, 2019; Grimmond et al., 2020), Urban Heat Island Observation, Modeling, and Monitoring Systems (WMO, 2023a), and Multi-Hazard Early Warning Systems (MHEWS) (Tang et al., 2021)—provide a strong foundation for developing urban-scale models that address the complexities of urban environments and their adaptation needs (WMO, 2023b). Beyond incorporating climate change projections, these models should also facilitate the evaluation and comparison of different adaptation strategies to inform decision-making.

We advocate for highly developed cities to take a leading role in advancing urban-scale climate modeling. A notable initiative in this direction is the ongoing development of models for the Shanghai megacity and the Yangtze River Delta urban agglomeration, led by the WMO GURME in collaboration with Fudan University and other partners (Tang, 2006; Tan et al., 2015). Additionally, four other demonstration cities across different continents—Hong Kong, Mexico City, Paris, and Toronto—have been studied as reference cases (Baklanov et al., 2020).

By leveraging their resources and expertise, these cities can serve as global leaders in urban climate modeling, sharing best practices, open-source tools, and case studies to support broader adoption. Through leadership and collaboration, highly developed cities can not only strengthen their own resilience but also drive global progress toward sustainable, climate-adaptive urban development.

## 3 Conclusions

Advancing local-scale models presents multifaceted challenges, including data scarcity, model resolution constraints, and the complexity of simulating local dynamic processes. Addressing these issues requires sustained efforts in data integration, continuous model refinement, and strengthened interdisciplinary collaboration.

Ongoing international projects and initiatives, including the Coordinated Regional Climate Downscaling Experiment (CORDEX), Urban Environments and Regional Climate Change (URB-RCC), Pan-Eurasian Experiment (PEEX), Climate-Resilient Development Pathways in Metropolitan Areas in Europe (CARMINE), Integrated Systems and Analysis of Urban Mobility for Climate-Neutral and Sustainable Cities in Europe and China (IMTECC), and WMO-led Global Framework for Climate Services (GFCS), are actively contributing to capacity building and the provision of tailored climate information. These projects highlight the importance of collaborative, cross-regional efforts in supporting climate resilience.

Looking ahead, future research and development of local-scale modeling should prioritize:

(1) the development of scalable, seamless, fit-for-purpose local-scale models;

(2) the integration of AI and machine learning to enhance model performance;

(3) improved representation of local socio-environmental interactions.

Given the growing and intensifying impacts of climate change across diverse regions, the urgency of developing advanced local-scale modeling tools is evident. By investing in these models, policymakers, scientists, and communities can collaborate to design targeted adaptation strategies that address region-specific challenges. We advocate a concerted effort to prioritize and accelerate the advancement of local-scale models, fostering a more resilient and adaptive response to the complex and evolving challenges posed by climate change.



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## References

Alapaty K, Mathur R, Pleim J, Hogrefe C, Rao S, Ramaswamy V, Galmarini S, Schaap M, Makar P, Vautard R, et al. (2012). New Directions: Understanding interactions of air quality and climate change at regional scales. Atmospheric Environment, 49: 419–421

Baklanov A, Brunner D, Carmichael G, Flemming J, Freitas S, Gauss M, Hov Ø, Mathur R, Schlünzen K H, Seigneur C, et al. (2017a). Key issues for seamless integrated chemistry–meteorology modeling. Bulletin of the American Meteorological Society, 98(11): 2285–2292

Baklanov A, Cárdenas B, Lee T C, Leroyer S, Masson V, Molina L T, Müller T, Ren C, Vogel F R, Voogt J A (2020). Integrated urban services: experience from four cities on different continents. Urban Climate, 32: 100610

Baklanov A, Grimmond C S B, Carlson D, Terblanche D, Tang X, Bouchet V, Lee B, Langendijk G, Kolli R K, Hovsepyan A (2018). From urban meteorology, climate and environment research to integrated city services. Urban Climate, 23: 330–341

Baklanov A, Korsholm U S, Nuterman R, Mahura A, Nielsen K P, Sass B H, Rasmussen A, Zakey A, Kaas E, Kurganskiy A, et al. (2017b). Enviro-HIRLAM online integrated meteorology–chemistry modelling system: strategy, methodology, developments and applications (v7.2). Geoscientific Model Development, 10(8): 2971–2999

Baklanov A, Zhang Y (2020). Advances in air quality modeling and forecasting. Global Transitions, 2: 261–270

Bi K F, Xie L X, Zhang H H, Chen X, Gu X T, Tian Q (2023). Accurate medium-range global weather forecasting with 3D neural networks. Nature, 619(7970): 533–538

Biesbroek R, Lesnikowski A (2018). Adaptation: The neglected dimension of polycentric climate governance? In: Jordan A, Huitema D, van Asselt H, Forster J, eds. Governing climate change: polycentricity in action? Cambridge: Cambridge University Press, 303–319

Ching J, Aliaga D, Mills G, Masson V, See L, Neophytou M, Middel A, Baklanov A, Ren C, Ng E, et al. (2019). Pathway using WUDAPT's digital synthetic city tool towards generating urban canopy parameters for multi-scale urban atmospheric modeling. Urban Climate, 28: 100459

Ching J, Mills G, Bechtel B, See L, Feddema J, Wang X, Ren C, Brousse O, Martilli A, Neophytou M, et al. (2018). WUDAPT: an urban weather, climate, and environmental modeling infrastructure for the Anthropocene. Bulletin of the American Meteorological Society, 99(9): 1907–1924

Creutzig F, Lohrey S, Bai X M, Baklanov A, Dawson R, Dhakal S, Lamb W F, McPhearson T, Minx J, Munoz E, et al. (2019). Upscaling urban data science for global climate solutions. Global Sustainability, 2: e2

Dafouf S, Lahrach A, Tabyaoui H, Benaabidate L (2025). Future evolutions of precipitation and temperature using the statistical downscaling model (SDSM), case of the Guir and the Ziz watershed, morocco. Earth, 6(1): 4

Danabasoglu G, Lamarque J F, Bacmeister J, Bailey D A, DuVivier A K, Edwards J, Emmons L K, Fasullo J, Garcia R, Gettelman A, et al. (2020). The community earth system model version 2 (CESM2). Journal of Advances in Modeling Earth Systems, 12(2): e2019MS001916

Dee D, Obregon A, Buontempo C (2024). Are our climate data fit for your purpose? Bulletin of the American Meteorological Society, 105(9): E1723–E1733

Delgado J M, Merz B, Apel H (2014). Projecting flood hazard under climate change: an alternative approach to model chains. Natural Hazards and Earth System Sciences, 14(6): 1579–1589

Demuzere M, Kittner J, Bechtel B (2021). LCZ generator: a web application to create local climate zone maps. Frontiers in Environmental Science 9: 637455

Demuzere M, Kittner J, Martilli A, Mills G, Moede C, Stewart I D, van Vliet J, Bechtel B (2022). A global map of local climate zones to support earth system modelling and urban-scale environmental science. Earth System Science Data, 14(8): 3835–3873

Estrada F, Calderón-Bustamante O, Botzen W, Velasco J A, Tol R S J (2022). AIRCC-Clim: a user-friendly tool for generating regional probabilistic climate change scenarios and risk measures. Environmental Modelling & Software, 157: 105528

Fowler H J, Blenkinsop S, Tebaldi C (2007). Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology, 27(12): 1547–1578

Ganguly A R, Kodra E A, Agrawal A, Banerjee A, Boriah S, Chatterjee S, Chatterjee S, Choudhary A, Das D, Faghmous J, et al. (2014). Toward enhanced understanding and projections of climate extremes using physics-guided data mining techniques. Nonlinear Processes in Geophysics, 21(4): 777–795

Gentine P, Pritchard M, Rasp S, Reinaudi G, Yacalis G (2018). Could machine learning break the convection parameterization deadlock? Geophysical Research Letters, 45(11): 5742–5751

Giorgi F, Jones C, Asrar G R (2009). Addressing climate information needs at the regional level: the CORDEX framework. WMO Bulletin, 58(3): 175–183

Giorgi F, Mearns L O (1999). Introduction to special section: regional climate modeling revisited. Journal of Geophysical Research: Atmospheres, 104(D6): 6335–6352

Grimmond S, Bouchet V, Molina L T, Baklanov A, Tan J G, Schlünzen K H, Mills G, Golding B, Masson V, Ren C, et al. (2020). Integrated urban hydrometeorological, climate and environmental services: concept, methodology and key messages. Urban Climate, 33: 100623

Gutowski Jr W J, Ullrich P A, Hall A, Leung L R, O'Brien T A, Patricola C M, Arritt R W, Bukovsky M S, Calvin K V, Feng Z, et al. (2020). The ongoing need for high-resolution regional climate models: process understanding and stakeholder information. Bulletin of the American Meteorological Society, 101(5): E664–E683

Hay L E, Wilby R L, Leavesley G H (2000). A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. JAWRA Journal of the American Water Resources Association, 36(2): 387–397

Hobeichi S, Nishant N, Shao Y W, Abramowitz G, Pitman A, Sherwood S, Bishop C, Green S (2023). Using machine learning to cut the cost of dynamical downscaling. Earth's Future, 11(3): e2022EF003291

Huang G, Wang Y, Ham Y G, Mu B, Tao W C, Xie C Y (2024). Toward a learnable climate model in the artificial intelligence era. Advances in Atmospheric Sciences, 41(7): 1281–1288

IPCC (Intergovernmental Panel on Climate Change) (2021). Summary for policymakers. In: Masson-Delmotte V, Zhai P, Pirani A, Connors S L, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis M I, eds. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press, 2391

Jungclaus J H, Lorenz S J, Schmidt H, Brovkin V, Brüggemann N, Chegini F, Crüger T, De-Vrese P, Gayler V, Giorgetta M A, et al. (2022). The ICON earth system model version 1.0. Journal of Advances in Modeling Earth Systems, 14(4): e2021MS002813

Karniadakis G E, Kevrekidis I G, Lu L, Perdikaris P, Wang S F, Yang L (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6): 422–440

Koldunov N, Jung T (2024). Local climate services for all, courtesy of large language models. Communications Earth & Environment, 5(1): 13

Kulmala M, Lappalainen H K, Petäjä T, Kurten T, Kerminen V M, Viisanen Y, Hari P, Sorvari S, Bäck J, Bondur V, et al. (2015). Introduction: the Pan-Eurasian Experiment (PEEX) – multi-disciplinary, multiscale and multicomponent research and capacity-building initiative. Atmospheric Chemistry and Physics, 15(22): 13085–13096

Lam R, Sanchez-Gonzalez A, Willson M, Wirnsberger P, Fortunato M, Alet F, Ravuri S, Ewalds T, Eaton-Rosen Z, Hu W H, et al. (2023). Learning skillful medium-range global weather forecasting. Science, 382(6677): 1416–1421

Langendijk G S, Halenka T, Hoffmann P, Adinolfi M, Campino A A, Asselin O, Bastin S, Bechtel B, Belda M, Bushenkova A, et al. (2024). Towards better understanding the urban environment and its interactions with regional climate change: the WCRP CORDEX flagship pilot study URB-RCC. Urban Climate, 58: 102165

Liu Z, Gao S, Cai W J, Li Z Y, Wang C, Chen X, Ma Z Y, Zhao Z J (2023). Projections of heat-related excess mortality in China due to climate change, population and aging. Frontiers of Environmental Science & Engineering, 17(11): 132

Lopez-Gomez I, Wan Z Y, Zepeda-Núñez L, Schneider T, Anderson J, Sha F (2025). Dynamical-generative downscaling of climate model ensembles. Proceedings of the National Academy of Sciences of the United States of America, 122(17): e2420288122

Mahura A, Baklanov A, Makkonen R, Boy M, Petäjä T, Lappalainen H K, Nuterman R, Kerminen V M, Arnold S R, Jochum M, et al. (2024). Towards seamless environmental prediction – development of Pan-Eurasian EXperiment (PEEX) modelling platform. Big Earth Data, 8(2): 189–230

MEGAPOLI (2010). Hierarchy of urban canopy parameterisations for different scale models. MEGAPOLI Scientific Report 10-04. Copenhagen: Danish Meteorological Institute

Michalek A T, Villarini G, Kim T (2024). Understanding the impact of precipitation bias-correction and statistical downscaling methods on projected changes in flood extremes. Earth's Future, 12(3): e2023EF004179

Mills G, Arunachalam S, Shi Y, Baklanov A (2024). Jason Ching and the development of an urban climate science: an introduction to the special issue on the world urban database access portal tools (WUDAPT). Urban Climate, 58: 102179

Murphy J M, Harris G R, Sexton D M H, Kendon E J, Bett P E, Clark R T, Eagle K, Fosser G, Fung F, Lowe J A, et al. (2018) UKCP18 Land Projections: Science Report. Exeter: Met Office of UK

Ouyang H L, Tang X, Kumar R, Zhang R H, Brasseur G, Churchill B, Alam M, Kan H D, Liao H, Zhu T, et al. (2022a). Toward better and healthier air quality: implementation of WHO 2021 global air quality guidelines in Asia. Bulletin of the American Meteorological Society, 103(7): E1696–E1703

Ouyang H L, Tang X, Zhang R H (2022b). Research themes, trends and future priorities in the field of climate change and health: a review. Atmosphere, 13(12): 2076

Ouyang H L, Tang X, Zhang R H, Baklanov A, Brasseur G, Kumar R, Han Q L, Luo Y (2023). Resilience building and collaborative governance for climate change adaptation in response to a new state of more frequent and intense extreme weather events. International Journal of Disaster Risk Science, 14(1): 162–169

Pfister G G, Eastham S D, Arellano A F, Aumont B, Barsanti K C, Barth M C, Conley A, Davis N A, Emmons L K, Fast J D, et al. (2020). The multi-scale infrastructure for chemistry and aerosols (MUSICA). Bulletin of the American Meteorological Society, 101(10): E1743–E1760

Pierce D W, Cayan D R, Das T, Maurer E P, Miller N L, Bao Y, Kanamitsu M, Yoshimura K, Snyder M A, Sloan L C, et al. (2013). The key role of heavy precipitation events in climate model disagreements of future annual precipitation changes in California. Journal of Climate, 26(16): 5879–5896

Potter S H, Kox T, Mills B, Taylor A, Robbins J, Cerrudo C, Wyatt F, Harrison S, Golding B, Lang W, et al. (2025). Research gaps and challenges for impact-based forecasts and warnings: Results of international workshops for High Impact Weather in 2022. International Journal of Disaster Risk Reduction, 118: 105234

Reichstein M, Camps-Valls G, Stevens B, Jung M, Denzler J, Carvalhais N, Prabhat (2019). Deep learning and process understanding for data-driven earth system science. Nature, 566(7743): 195–204

SC (2023). The State Council Information Office Held a Press Conference on the First National Comprehensive Risk Survey of Natural Disasters . Beijing: The State Council of the People's Republic of China

Semenov M A, Barrow E M (1997). Use of a stochastic weather generator in the development of climate change scenarios. Climatic Change, 35(4): 397–414

Skamarock W C, Klemp J B, Dudhia J, Gill D O, Barker D M, Duda M G, Huang X, Wang W, Powers J G (2008). A Description of the Advanced Research WRF Version 3. Tech. Note, NCAR/TN-475+STR. Boulder: National Center for Atmospheric Research

Song X K, Zhang S H, Huang H, Ding Q, Guo F, Zhang Y X, Li J, Li M Y, Cai W J, Wang C (2024). A systematic review of the inequality of health burdens related to climate change. Frontiers of Environmental Science & Engineering, 18(5): 63

Stewart I D, Oke T R (2012). Local climate zones for urban temperature studies. Bulletin of the American Meteorological Society, 93(12): 1879–1900

Tamayo J, Rodriguez-Camino E, Hernanz A, Covaleda S (2022). Downscaled climate change scenarios for central America. Advances in Science and Research, 19: 105–115

Tan J G, Yang L M, Grimmond C S B, Shi J P, Gu W, Chang Y Y, Hu P, Sun J, Ao X Y, Han Z H (2015). Urban integrated meteorological observations: practice and experience in Shanghai, China. Bulletin of the American Meteorological Society, 96(1): 85–102

Tang X (2006). Managing disaster risk in a mega-city. WMO Bulletin, 55(4): 268–273

Tang X, Sassa K, Brasseur G P, Cullmann J, Fang Z Q (2021). Collaboration in MHEWS through an integrated way. In: Sassa K, Mikoš M, Sassa S, Bobrowsky P T, Takara K, Dang K, eds. Understanding and Reducing Landslide Disaster Risk. Cham: Springer, 479–497.

Wang X, Tolksdorf V, Otto M, Scherer D (2021). WRF-based dynamical downscaling of ERA5 reanalysis data for high mountain Asia: towards a new version of the High Asia Refined analysis. International Journal of Climatology, 41(1): 743–762

WEF (2024). Global Risks Report 2024. 19th Edition. Geneva: World Economic Forum

Werner A T, Cannon A J (2016). Hydrologic extremes: an intercomparison of multiple gridded statistical downscaling methods. Hydrology and Earth System Sciences, 20(4): 1483–1508

Wilby R L, Dawson C W, Barrow E M (2002). SDSM: a decision support tool for the assessment of regional climate change impacts. Environmental Modelling & Software, 17(2): 145–157

WMO (2015). Seamless Prediction of the Earth System: from Minutes to Months. WMO-No.1156. Geneva: World Meteorological Organization

WMO (2018). Step-by-Step Guidelines for Establishing a National Framework for Climate Services. WMO-No.1206. Geneva: World Meteorological Organization

WMO (2019). Guidance on Integrated Urban Hydrometeorological, Climate and Environmental Services, Volume I: Concept and Methodology. WMO-No.1234. Geneva: World Meteorological Organization

WMO (2023a). Guidance on Measuring, Modelling and Monitoring the Canopy Layer Urban Heat Island (CL-UHI). WMO-No.1292. Geneva: World Meteorological Organization

WMO (2023b). Good Practices in High-Resolution Modelling for Integrated Urban Services. WMO-No.1313. Geneva: World Meteorological Organization

WMO (2025). WMO Confirms 2024 as Warmest Year on Record at About 1.55 °C Above Pre-Industrial Level. Geneva: World Meteorological Organization

Wood A W, Leung L R, Sridhar V, Lettenmaier D P (2004). Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Climatic Change, 62(1−3): 189–216

Xie S P, Deser C, Vecchi G A, Collins M, Delworth T L, Hall A, Hawkins E, Johnson N C, Cassou C, Giannini A, et al. (2015). Towards predictive understanding of regional climate change. Nature Climate Change, 5(10): 921–930

Yang J, Yu W B, Baklanov A, He B J, Ge Q S (2025). Mainstreaming the local climate zone framework for climate-resilient cities. Nature Communications, 16(1): 5705

Yoshikane T, Yoshimura K (2023). A downscaling and bias correction method for climate model ensemble simulations of local-scale hourly precipitation. Scientific Reports, 13(1): 9412

Yuval J, O’Gorman P A (2020). Stable machine-learning parameterization of subgrid processes for climate modeling at a range of resolutions. Nature Communications, 11(1): 3295

Zhang R H, Tang X, Liu J, Visbeck M, Guo H D, Murray V, Mcgillycuddy C, Ke B, Kalonji G, Zhai P M, et al. (2022). From concept to action: a united, holistic and One Health approach to respond to the climate change crisis. Infectious Diseases of Poverty, 11(1): 17