Data Driven EnviroLab

Climate AI for Cities

Solutions for Mitigation, Adaptation, and Energy Access



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Executive Summary

As cities face intensifying climate risks, AI is increasingly being considered as a potential tool for mitigation, adaptation, and energy access goals. Yet, despite growing interest, credible AI applications in the climate change and sustainability domains are relatively fewer in number, pointing to a gap between the potential of AI for urban climate action and its deployment in practice.

This report provides a practical guide to the emerging landscape of Climate AI solutions for cities. It introduces a multi-dimensional Climate AI solutions framework to help cities assess solutions systematically across key dimensions such as input data required, technology readiness level, and AI category.

Several findings stand out. First, Climate AI solutions are varied in type and development level, ranging from open-source solutions that are often AI models or technical frameworks to "off-the-shelf" AI products or software that package underlying AI methods into a service. Second, the Climate AI solutions landscape is still maturing. More than half of the solutions in our database are still in the pilot or early adoption phase, with little transparency into the full implementation costs. Evidence of impact at scale is limited and the transferability of solutions across different urban contexts cannot be assumed. Third, the feasibility of a solution depends as much on a city's internal conditions as on the technical requirements of the tool itself. In our report, we discuss how cities need to consider their institutional capacity and whether they have sufficient, high-quality data for the implementation of some solutions. Lastly, cities must also navigate real risks including environmental costs, biased data, information integrity, and governance gaps around human oversight.

To support cities in navigating these challenges, this report provides guidance on identifying, evaluating, and adopting Climate AI solutions to address mitigation, adaptation, and energy access in cities. It provides cities with guidance on assessing their readiness for Climate AI adoption and on engaging with solution providers. Ultimately, it is important to note that AI might not always be the right tool for every urban climate context. Cities should approach adoption with clear objectives, realistic expectations, and a commitment to responsible, evidence-informed decision-making.

Introduction

Artificial intelligence (AI) is rapidly emerging as a tangible tool for climate action in cities. Housing more than half of the world's population, urban areas today account for up to 83% of global carbon dioxide emissions[1] while facing growing exposure to climate hazards such as flooding and extreme heat. This duality means that cities are highly vulnerable to climate risks while being uniquely positioned to drive meaningful climate action. While AI has been widely promoted as a tool that can potentially help cities with their climate goals, systematic evidence on which solutions are available, where they are most useful, and the challenges in implementing them remain limited.

Already, nearly half of 250 cities surveyed for a Deloitte report, "AI-powered Cities of the Future," responded that they plan to make "wide use" of traditional AI (or older AI methods or systems that perform specific, pre-programmed tasks using explicit rules and logic instead of learning from data,[2] such as "machine learning, computer vision, and natural language processing") by 2028, a substantial rise from 18% in 2025.[3] The top-reported use cases by domain include "government management and operations" (with 44% of cities responding that they actively use AI for this); "safety, security, and resilience" (42%); "urban infrastructure" (34%); and "living, health and trust" (33%).

However, only 22% of cities surveyed in this Deloitte study indicated that they are actively using AI for "environment and sustainability," thus underscoring the relative nascency of AI applications for climate action among cities. Among these 22% of cities currently using AI for "environment and sustainability," the most common applications lie in waste management and recycling, energy optimization, as well as water management and monitoring.

At the same time, a Google Scholar search of "AI cities climate applications" returned more than 800,000 results as of

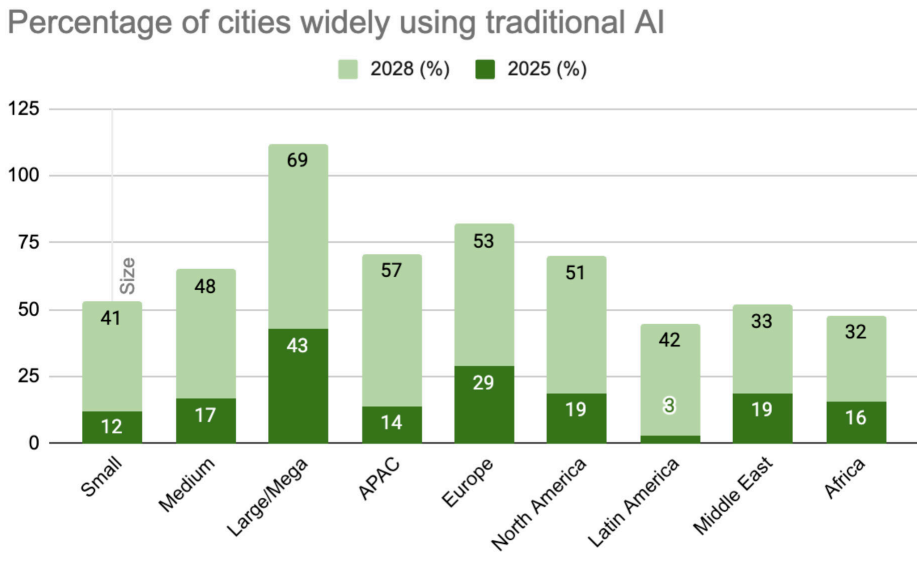


Figure 1. Data illustrating the projected increase in cities planning to expand their use of AI (Source: Deloitte, 2025).[4]

1 Ying, Y., Manya, D., and Hsu, A. (2026). Aligning emissions with decisionmaking: estimating urban contributions to global carbon dioxide emissions. Pre-print: https://doi.org/10.31223/X5PB02.

2 Stanford Institute for Human-Centered AI. (n.d.) What is Traditional AI? Stanford. https://hai.stanford.edu/ai-definitions/what-is-traditional-ai.

3 Deloitte. (2025). AI-Powered Cities of the Future. Deloitte. https://www.deloitte.com/us/en/industries/government-public/research/ai-powered-cities-of-future.html.

4 Deloitte. (2025). AI-Powered Cities of the Future. Deloitte. https://www.deloitte.com/us/en/industries/government-public/research/ai-powered-cities-of-future.html.

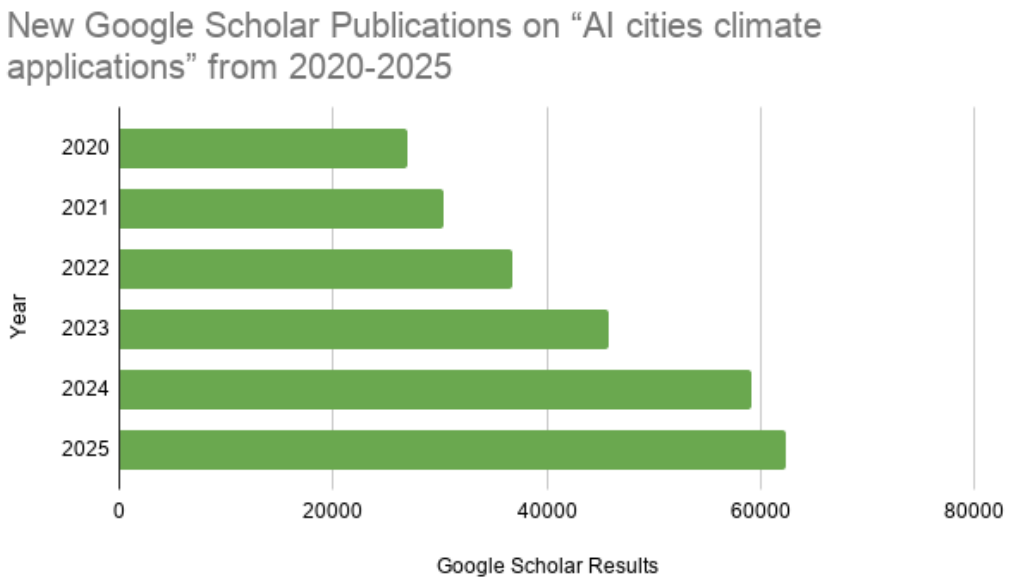


Figure 2. Data illustrating the growing academic literature on “AI cities climate applications” on Google Scholar.

April 2026, revealing a clear disconnect between how leading cities are primarily using AI and the growing academic literature on the use of AI for urban climate action.

Part of the challenge in extracting meaningful insights and scaling AI solutions to cities in diverse contexts is that “AI” is frequently conflated as a singular solution even though it encompasses a wide range of methods, data requirements, and use cases. In urban climate contexts, AI solutions can range from predictive models and control systems for buildings and energy usage to computer vision for traffic and waste management, natural language processing (NLP) and large language models (LLMs) for more efficient government administration, or generative AI (GenAI) for decision support. Recent research on AI-for-climate applications in European cities shows that the range of solutions spans very disparate technical systems and governance needs including waste-route optimizing, smart building energy controls, renewable energy forecasting, and text classification for building code analysis.[5]

Despite the range and diversity of potential solutions, implementation remains fragmented and uneven across cities around the world. Some cities are only beginning to consider what developments in AI will mean for climate solutions while other cities are actively piloting and implementing solutions in anticipation of a future increasingly shaped by AI.[6] The actors and institutions involved in developing and advancing AI solutions for climate action in cities are also diverse and shaped by a mix of private start-ups, large corporations, consultants, researchers, philanthropists, and governments. Existing evidence suggests that even relatively advanced cities face recurring bottlenecks,[7] including limited AI literacy within city administrations, weak data readiness, procurement and budget constraints, interoperability challenges with legacy

5 Hintz, M., Gross, M., Creutzig, F., and Kaack, L. (2026). Practical implementation of artificial intelligence for climate change mitigation in cities–priorities, collaborations and challenges. Energy Research & Social Science, 131, 104498. https://doi.org/10.1016/j.erss.2025.104498.

6 Govex. (2025). In City Ai Connect’s second year, cities turned from rule-setting to experimentation. John Hopkins University. https://govex.jhu.edu/blog/in-city-ai-connects-second-year-cities-turned-from-rule-setting-to-experimentation.

7 Hintz, M., Gross, M., Creutzig, F., and Kaack, L. (2026). Practical implementation of artificial intelligence for climate change mitigation in cities–priorities, collaborations and challenges. Energy Research & Social Science, 131, 104498. https://doi.org/10.1016/j.erss.2025.104498.

infrastructure, and uncertainty around governance.[8] These findings highlight that cities face not only technical barriers, but also significant capacity, organizational, and institutional challenges in the adoption of AI solutions in general.

These gaps are amplified outside of the high-income, data-rich contexts where most AI development and applications occur. For instance, the Data Provenance Initiative[9] found that North American and European organizations account for 93% of text tokens (e.g., a unit of data that LLMs use to process and generate new text) and more than 60% of speech and video hours in training data, while African and South American organizations account for less than 0.2% of training content. Furthermore, many cities in the Global South face very different realities, such as weaker digital and administrative infrastructure, large and growing informal settlements, and unreliable electricity access. AI solutions that rely on continuous sensor networks or locally-hosted cloud infrastructure may not be well suited for these contexts.

Against this backdrop, this report is intended as a practical guide to the emerging landscape of AI for urban climate action, particularly for mitigation, adaptation, and energy access. Through an evaluation framework that distinguishes between various AI solutions' methods, technology readiness level, and other indicators, such as feasibility of implementation, this report evaluates how solutions are deployed in practice and the climate goals they can support. It also evaluates the kinds of input data and the degree of institutional capacity needed to adopt and operate these solutions effectively. This framework is intended to help cities compare solutions more systematically and identify key considerations when determining whether and which AI tools are most appropriate for their climate goals, resource constraints, and implementation contexts.

8 Suleimany, M., Gonbad, M. R. S., Naghibizadeh, S., & Niri, S. D. (2025). Artificial intelligence as a tool for building more resilient cities in the climate change era: A systematic literature review. Artificial Intelligence and Machine Learning Applications for Sustainable Development, 60-81

9 Longpre, S., et al. (2024). Bridging the data provenance gap across text, speech and video. arXiv preprint arXiv:2412.17847.

Box 1. Key AI concepts and terms

Artificial Intelligence (AI) refers to "computer systems that can perform complex tasks normally done by human-reasoning and decision making" without significant human oversight.[10] AI is a broad technology whose applications have grown increasingly sophisticated and diverse alongside the exponential rise in computational power over the past few decades.

Agentic AI is an "artificial intelligence system that can accomplish a specific goal with limited supervision."[11] It consists of models that mimic human actors and act independently according to predetermined instructions, guidelines, and prompts. Currently, agentic AI is considered a relatively nascent technology and requires human oversight.

Machine Learning (ML) is a "subset of artificial intelligence concerned with training models to allow computers to mimic human thought and decision making without explicit programming."[12] Machine learning enables the analysis of datasets and identifies patterns within them to predict outcomes or produce outputs. Today, machine learning is the driving technical force behind many modern AI systems such as forecasting models, large language models, and other generative AI tools.[12]

Deep Learning (DL) is a specialized subset of machine learning that trains computers to "mimic the way neurons in the human brain process and learn information." Deep learning models power most state-of-the-art artificial intelligence today such as computer vision given their strength in processing unstructured data such as images, audio, and text.[13]

Generative AI, or GenAI, is AI technology that is capable of producing new content such as text, images, videos, audio, or code in response to a user prompt by drawing on patterns observed in training data.[14, 15] In urban climate contexts, generative AI has potential applications in public communication and the synthesis of complex datasets, although its high energy demands and tendency to produce "hallucinations" (i.e., plausible sounding but inaccurate outputs) require careful consideration.

Large Language Models (LLMs) are models trained on vast amounts of text data making them capable of processing, learning from, and generating human language. Essentially, "LLMs predict the probabilities of the next word (token), given an input string of text, based on the statistical properties of the language in the training data."[16]

Multimodal Large Language Models are more sophisticated LLM models capable of interacting with data in different forms or modes simultaneously – hence the term "multimodal" – including audio, images, videos and text. Multimodal LLMs are able to perceive, understand, and interact with the world more holistically, leading to more

10 NASA. (n.d.). What is artificial intelligence? NASA. https://www.nasa.gov/what-is-artificial-intelligence/.
11 Shahidi, P. et al. (2025). The Coasean Singularity? Demand, Supply, and Market Design with AI Agents. The Economics of Transformative AI. https://www.nber.org/books-and-chapters/economics-transformative-ai/coasean-singularity-demand-supply-and-market-design-ai-agents.
12 UC Berkeley School of Information. (2026). What Is Machine Learning (ML)? Definition and Examples. UC Berkeley. https://ischoolonline.berkeley.edu/blog/what-is-machine-learning/.
13 ISO. (n.d.). Deep learning: The mechanics of magic. ISO. https://www.iso.org/artificial-intelligence/deep-learning.
14 He, R., et al. (2025). Generative artificial intelligence: a historical perspective. National Science Review, Volume 12, Issue 5. https://doi.org/10.1093/nsr/nwaf050.
15 Feuerriegel, S., et al. (2024). Generative AI. Business & Information Systems Engineering, 66(1), 111-126. https://doi.org/10.1007/s12599-023-00834-7.
16 NYU Libraries. (n.d.). Machines and Society: What Large Language Models Are. NYU. https://guides.nyu.edu/c.php?g=1308742&p=9997824.

complex applications.[17]

Natural Language Processing (NLP) is a broad subfield focused on enabling computers to understand, interpret, process, and communicate using human language. NLP enables computers to perform tasks such as sentiment analysis, text classification, machine translation, chatbot development, and more.[18]

Optimization refers to the process of systematically fine-tuning a model's inputs and parameters so that it performs as well as possible against defined objectives such as minimizing prediction error. Optimization typically occurs during model training where small changes are repeatedly made to improve the model's accuracy.[19]

Classification in machine learning is a predictive modeling process where machine learning models use algorithms to predict the correct label or classification for any input data.[20] For example, a classification model might be trained to identify whether a satellite image shows tree cover, a solar panel, or bare concrete.

Computer Vision is a subfield of AI that enables machines to process, analyze, and interpret visual inputs such as images and videos. It achieves this by using machine learning to help computers derive meaningful information from visual data.[21]

Statistical methods draw on patterns observed in historical data to make inferences, predictions, or estimates about unknown or future outcomes. They are not necessarily AI methods but are foundational to many machine learning approaches. Because real-world data often contain noise, variability, and incomplete information, statistical outputs may be expressed probabilistically, such as ranges with confidence intervals, likelihoods, or estimated relationships rather than single fixed answers.[22]

Deterministic methods rely on fixed assumptions and can be thought of as mathematical representations that produce the same, precise output from a given set of inputs with no randomness involved. Deterministic methods are traditional mathematical, engineering, or rules-based approaches that are sometimes incorporated into AI pipelines, though they are not AI methods by nature. Unlike statistical methods, they do not incorporate randomness, probability, or uncertainty into their modeling assumptions, thus yielding consistent, repeatable results with the same inputs and conditions.[23]

Reinforcement Learning (RL) is a type of machine learning process in which autonomous agents learn to make better decisions by interacting with data inputs and their environment. In reinforcement learning, autonomous agents learn to perform a task and make optimal decisions by learning from trial-and-error without human input.[24]

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17 Wang, J., et al. (2024). A Comprehensive Review of Multimodal Large Language Models: Performance and Challenges Across Different Tasks. https://doi.org/10.48550/arXiv.2408.01319.

18 ISO. (n.d.). Unravelling the secrets of natural language processing. ISO. https://www.iso.org/artificial-intelligence/natural-language-processing.

19 Stanford University Human-Centered Artificial Intelligence. (n.d.). What is an Optimization Algorithm? Stanford University. https://hai.stanford.edu/ai-definitions/what-is-an-optimization-algorithm.

20 Keita, Z. (2024). Classification in Machine Learning: An Introduction. Datacamp. https://www.datacamp.com/blog/classification-machine learning.

21 Matsuzaka, Y., & Yashiro, R. (2023). AI-Based Computer Vision Techniques and Expert Systems. AI, 4(1), 289-302. https://doi.org/10.3390/ai4010013.

22 Robins, A. (2020). Stochastic vs Deterministic Models: Understand the Pros and Cons. EV. https://blog.ev.uk/stochastic-vs-deterministic-models-understand-the-pros-and-cons.

23 Rockett, D. (2025). Deterministic vs. probabilistic models: A guide for data teams. Rudderstack. https://www.rudderstack.com/blog/deterministic-vs-probabilistic/.

24 Sutton, R., & Barto, A. (2018). Reinforcement Learning: An Introduction. MIT Press: Cambridge. https://web.stanford.edu/class/psych209/Readings/SuttonBartoIPRLBook2ndEd.pdf.

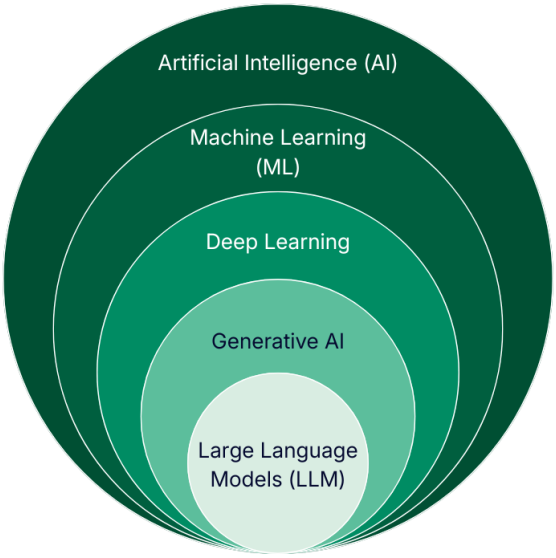


Figure 3. An overview of the subsets and layers within "AI."

Defining 'Climate AI' - What does this mean for cities?

AI is often discussed as a single technology or solution. However, this conflation can be misleading. While AI has been broadly defined as a "technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy,"[25] AI encompasses a wide range of methods, models, and products with very different data requirements, use cases, and applications. In fact, many current "AI solutions" are grounded in older, well-established statistical or deterministic methods that are further augmented by modern computing capacity and reinforcement learning.

These definitions matter because AI can often be misrepresented, either intentionally or otherwise, making it harder for cities to accurately evaluate what a solution actually does and whether it is genuinely suited for their climate goals. Reuters has reported on recent trends where smaller companies are rebranding themselves as AI businesses to improve their market perception and attract investments.[26] This trend has been described as "AI-Washing," whereby organizations engage in "misleading and deceptive behavior, typically in the form of false or exaggerated claims about the use of AI or algorithmic systems in the business or its products or services."[27]

This problem is compounded by how many AI solutions essentially operate as black boxes, where the reasoning and underlying technologies driving their outputs can be difficult to identify even when the solution is functioning as intended. Solution providers might not have the incentive to be transparent about the models or assumptions underlying their technology to preserve a competitive advantage. For city officials, this opacity makes it hard to assess whether a solution is truly appropriate for their needs and whether it might introduce unintended risks.

It is important to note that AI solutions vary significantly in their resource consumption, reliability, and outputs depending

25 Stryker, C., and Kavlakoglu, E. (n.d.). What is artificial intelligence (AI)? IBM. https://www.ibm.com/think/topics/artificial-intelligence.
26 Agarwal, P., and Tripathy, A. (2026). US companies that jumped ship to tech, AI businesses over the years. Reuters. https://www.reuters.com/business/us-companies-that-jumped-ship-tech-ai-businesses-over-years-2026-04-16/.
27 Watal, A. (n.d.). AI-Washing: Are Buyers Being Taken to the Cleaners? Marketing Profs. https://www.marketingprofs.com/articles/2024/51593/ai-washing-deceptive-ai-marketing-risks.

on their underlying assumptions, modeling approaches, and training data used. Without a clear understanding of these differences, cities risk being locked into tools with hidden or unexpected financial, operational, and environmental costs that might ultimately undermine the climate goals the solutions are intended to support. In addition, without knowing what type of AI a solution actually uses, cities cannot accurately gauge potential associated risks, where errors might occur, and whether the solution is genuinely suited for their needs and goals.

For cities considering the adoption of AI solutions, this context underscores the importance of looking beyond marketing language to having a basic understanding of the technology underpinning the solution. While not every city staff needs to be a technical expert, cities should develop at least some internal expertise or familiarity with emerging AI technologies to help critically evaluate vendor claims and potential risks. Identifying and understanding the analytical approach underlying a solution – whether it involves AI, a specific kind of statistical modeling, or other computational methods – is crucial when considering the adoption of AI solutions. Different technical approaches rely on different assumptions, require different types of data, and produce different kinds of uncertainty and biases. Therefore, understanding the method behind a solution helps decision-makers interpret findings appropriately, recognize where caveats might be necessary, and assess whether a proposed solution is reliable, actionable, and appropriate for their use cases. For example, supervised machine learning models can be used to predict energy demand and improve building energy performance; optimization models can be used to identify more efficient control strategies; and deterministic engineering models can simulate building performance under different defined assumptions. In these cases, each approach produces different kinds of outputs and requires different forms of validation.

Other applications such as AI solutions for traffic management may rely on computer vision to detect vehicle flows, optimization models to adjust signal timing, or predictive analytics to anticipate congestion. Flood and heat risk tools may combine historical observations, remote sensing, climate projections, and deep learning methods to predict future exposure, but their results must be interpreted in light of data gaps, model uncertainty, and changing climate conditions. Beyond these applications, LLMs and generative AI chatbots may support government operations by streamlining communication, permitting processes, and public feedback channels. However, while these applications may improve efficiency, they can also introduce different risks related to factual accuracy, hallucinations, and algorithmic bias. In addition, digital or AI solutions may disadvantage and exclude residents with limited digital access or skills (e.g., the elderly or people with disabilities), those who prefer in-person assistance, and individuals who distrust AI technologies.[28]

In this report, we refer to "Climate AI" as AI solutions, tools, and resources primarily designed to support climate-related goals, especially for mitigation, adaptation, and energy access. It is distinct from "green AI," which focuses on making AI systems themselves less resource-intensive through efforts such as utilizing low-power architectures and model optimization.[29] While the two are complementary – and some Climate AI solutions might be built with green AI principles – the focus of this report is on Climate AI as a tool for urban climate action rather than how AI itself can be made greener.

The Climate AI solutions evaluated are concentrated primarily in machine learning and deep learning models, reflecting

28 Barroca, J., & Kishnani, P. (2023). Three ways people aged 55 and above access digital government services differently from those between 18 and 34. Deloitte Center for Government Insights. https://www.deloitte.com/us/en/insights/industry/government-public-sector-services/digital-government-services-technology-use-among-seniors.html.

29 Peykani, P., et al. (2026). Green Artificial Intelligence: A Comprehensive Review of Metrics, Tools, Challenges, Trends, and Future Prospects. Arch Computat Methods Eng. https://doi.org/10.1007/s11831-026-10546-2.

the current status of most urban climate applications.[30] Although generative AI (GenAI) approaches have risen in popularity due to the growth of chatbots like ChatGPT, Gemini, and Claude, the existing literature provides less evidence of cities using GenAI or LLM-based tools directly for climate action. Where cities have adopted these tools, they appear more commonly in general municipal functions, such as resident-facing chatbots for administrative purposes and public inquiries rather than in climate-specific applications. Box 2, which includes selected case studies on AI applications in cities, also provides an example of a text-based AI tool being used to monitor emerging climate disasters and deliver early warnings to users in Indonesia.

In practice, most evidence of Climate AI applications in cities points to the use of AI for tasks such as pattern detection and prediction in large datasets (e.g., flooding, heat, or air quality), the automation of routine analytical work, and forecast generation where repetitive and sufficient structured data exist.[31] These capabilities can support cities in advancing their climate mitigation, adaptation, and energy access goals. At the same time, it is important to note that not every climate challenge requires an AI solution, and when AI is relevant, the most complex AI solution may not be the most appropriate.

Traditional statistical models, deterministic methods, or simpler rule-based approaches may sometimes be sufficient and are often more transparent, easier to validate, and better suited to local institutional needs and constraints. Understanding this distinction and choosing the most appropriate approach is important because complex AI systems can be difficult to interpret, explain, or scrutinize especially for non-technical decision-makers and the communities they serve. In the context of urban climate action, where stakeholder trust and public buy-in are essential, cities should avoid adopting AI simply to signal innovation. Instead, they should assess whether the AI method is appropriate for the problem, whether its assumptions and uncertainties can be understood, and whether its outputs can be responsibly used in decision-making.

30 Yigitcanlar, T., et al. (2024). Unlocking Artificial Intelligence Adoption in Local Governments: Best Practice Lessons from Real-World Implementations. Smart Cities, 7(4), 1576-1625. https://doi.org/10.3390/smartcities7040064.

31 Adaptation Fund. et al. (2024). Use of Artificial Intelligence in Climate Change Evaluations. Adaptation Fund. https://www.adaptation-fund.org/wp-content/uploads/2025/03/Scoping-Study-on-Use-of-AI-in-Evaluations-03.24.25v2.pdf.

Box 2. AI applications in cities



Fortaleza, Brasil – AI-Powered monitoring to build a bike-friendly city

Fortaleza, Brasil's fourth-largest city by population and its most densely populated state capital, has long grappled with severe traffic congestion and one of the highest traffic fatality rates in the country.[32] In the early 2010s, the city made tackling urban congestion a strategic priority by investing in expanded public transport and bike-friendly infrastructure as part of a broader commitment to more equitable and sustainable urban development.

As part of this effort, Fortaleza deployed AI-powered tools to better plan and build bicycle pathways. Using real-time data dissemination and analytical counting, the city monitored where bicycles were used most frequently to better plan the expansion of bike lanes. This effort was also coupled with a public awareness campaign, a reduction in vehicle speed limits in certain hotspots, and partnerships with governmental departments and local businesses to encourage biking.[33]

While approaches such as real-time monitoring and analytical counting are not new nor unique to AI, the adoption of AI-enabled tools enabled Fortaleza to gather and utilize data to improve its urban mobility. Though it is difficult to quantify and report on the emissions mitigated through the adoption of this tool, the AI-monitoring system has helped Fortaleza to plan and build a more bike-friendly city with associated co-benefits, such as improved air quality and increased physical activity amongst residents.

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32 Linke, C. (2018). Fortaleza's Progress Shows that Change is Still Possible in Brazil. ITDP. https://itdp-indonesia.org/wp-content/uploads/2019/01/ST_30_FINAL_.pdf.

33 World Health Organization. (2021). Encouraging cycling in the city, Fortaleza, Brazil. WHO. https://www.who.int/news-room/featurestories/detail/encouraging-cycling-in-the-city-fortaleza-brazil.



Raleigh, U.S. – Understanding the role of AI in Raleigh's digital twin project

In 2025, the city of Raleigh in North Carolina announced a partnership with external vendors such as Esri, Nvidia, and Microsoft to develop a digital twin (i.e., a dynamic, virtual replica of a physical system such as a city or facility updated with real-time data for monitoring, simulation, and analysis)[34] with stated goals such as to better understand "traffic flows and impacts"[35] for better urban planning and management.[36]

Media outlets, including the Wall Street Journal,[37] have presented AI as a prominent feature of Raleigh's digital twin project. Yet, other publicly available descriptions of the project suggest a more modest technological implementation. Nvidia's case study about Raleigh, for instance, describes the visualization of sensor data onto a "3D interactive map" as a "digital twin,"[38] though the functionalities mentioned resemble an interactive geospatial dashboard rather than a high-fidelity digital twin.

While AI may play a role in parts of the data pipeline, including data collection and analysis, a standard digital twin typically consists of Internet of Things (IoT) sensors, high-performance computing infrastructure, trained personnel, and related systems that can deliver high-fidelity, real-time simulation capabilities. These capabilities and infrastructure do not seem to appear in Raleigh's context. Raleigh illustrates part of the broader challenge in the Climate AI landscape: terms such as "AI" and "digital twin" are used so widely that it becomes a challenge for cities and stakeholders to assess what technologies are actually being deployed, what inputs these solutions require, and what outputs and utility the solutions ultimately deliver.

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34 Gallagher, N., Armstrong, M. (2025). What is a digital twin? IBM. https://www.ibm.com/think/topics/digital-twin.
35 AEC Magazine. (n.d.). City of Raleigh using AI to gain insight into traffic. AEC Magazine. https://aecmag.com/digital-twin/raleigh-using-ai-to-gain-insight-into-city-traffic/.
36 City of Raleigh. (2024). Utilizing data for innovative solutions. City of Raleigh. https://raleighnc.gov/apps-maps-and-open-data/services/utilizing-data-innovative-solutions.
37 Marks, A. (2025). With AI, Cities Can Drive Resilience, Energy Efficiency: 3 Case Studies. Wall Street Journal. https://deloitte.wsj.com/cio/with-ai-cities-can-drive-resilience-energy-efficiency-3-case-studies-476e6e18.
38 Nvidia. (n.d.). How Raleigh Enhances City Safety and Mobility with Physical AI. Nvidia. https://www.nvidia.com/en-us/case-studies/raleigh-smart-city/.



Drancy, France – Integrating AI with existing infrastructure and scaling implementation by empowering staff

One of the first AI projects in Drancy, a commune of 35,000 people in the northeastern suburbs of Paris, was the retrofitting of its existing network of 200 video cameras (originally installed in 2004) with in-house AI software to detect littering.[39]

Building on that experience, Drancy expanded its use of AI to address other municipal needs. For example, Drancy started a project to equip existing waste disposal trucks with AI-enabled cameras to detect and classify incorrectly sorted waste in real-time and implemented an AI-powered traffic management system to optimize local traffic flow.[40] Additionally, during local elections, Drancy developed an AI-powered chatbot to answer questions by residents such as the validity of an identification document for voting while adopting digital technologies to assist with electronic voting, thus resulting in significant time savings. While Drancy's IT director pointed out that most of their staff are "far from being techies," Drancy has encouraged a culture of learning among its staff in its drive to become a smarter city.[41]

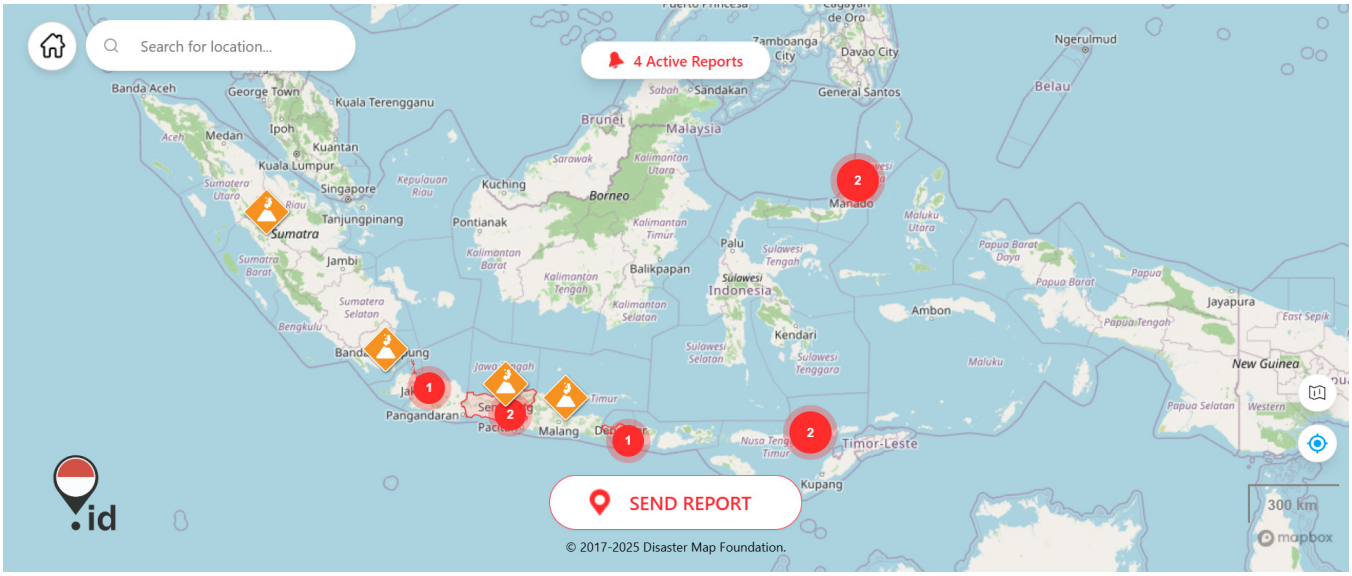
Though the adoption of digital technologies for voting is not necessarily AI-related, Drancy's approach towards the adoption of technology and AI for its municipal functions illustrates how even smaller cities and municipalities can pilot AI solutions and scale them incrementally across different functions without needing to significantly overhaul existing infrastructure. Despite being a relatively small commune, Drancy has empowered its staff to adopt technology to improve municipal functions and better serve residents by fostering a culture of continuous learning.

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39 Deloitte. (2025). AI-Powered Cities of the Future. Deloitte. https://www.deloitte.com/us/en/industries/government-public/research/ai-powered-cities-of-future.html.

40 Jones, J. (2025). AI cameras used to track household recycling errors in France. The Connexion. https://www.connexionfrance.com/news/ai-cameras-used-to-track-household-recycling-errors-in-france/723955.

41 Davan-Soulas, M. (2024). Intelligence artificielle, iPad... Comment Drancy est devenu un laboratoire des élections connectées. BFM Tech. https://www.bfmtv.com/tech/vie-numerique/intelligence-artificielle-i-pad-comment-drancy-est-devenu-un-laboratoire-des-elections-connectees_AN-202406090032.html.



Indonesia subnational regions – AI chatbots for natural disaster detection in data-scarce contexts

PetaBencana.id, or "disaster map," is a natural disaster warning system developed by Yayasan Peta Bencana (Disaster Map Foundation), a non-profit organization based in Indonesia.[42] Because local government resources and data availability are limited, natural disasters can cause more severe impacts given the lack of capable early warning systems. To address this, PetaBencana uses AI and internet bots to monitor, scrape, and analyze social media content that might signal emerging natural disasters across communities. In addition, the non-profit has also deployed AI-assisted "humanitarian chatbots" on apps such as WhatsApp where citizens can provide warnings about emerging disasters.[43]

These data points enable the real-time mapping of floods, fires, earthquakes, and other natural disasters in Indonesia, providing timely and critical updates for both emergency responders and residents. The organization's warning system was developed in partnership with local universities and has since been adopted as an official data provider for Indonesia's National Emergency Management Agency (BNPB).[44]

As an example of an open-source solution, PetaBencana was chosen as a case-study to highlight the use of LLMs for urban climate action and how community-specific AI tools can be developed through locally-grounded partnerships and participatory data collection.

42 Taylor, M. (2020). How chatbots and AI are helping Indonesia with disaster preparedness. GCA. https://gca.org/how-chatbots-and-ai-are-helping-indonesia-with-disaster-preparedness/#:~:text=PetaBencana.id%2C%20which%20means%20%E2%80%9C,and%20earthquakes%20in%20real%2Dtime.

43 Peta Bencana. (2023). Ahead of extreme monsoon weather, Indonesia launches first WhatsApp Humanitarian Chatbot. Peta Bencana. https://info.petabencana.id/230131.

44 Peta Bencana. (n.d.). About Yayasan Peta Bencana [Disaster Map Foundation]. Peta Bencana. https://info.petabencana.id/about-2.

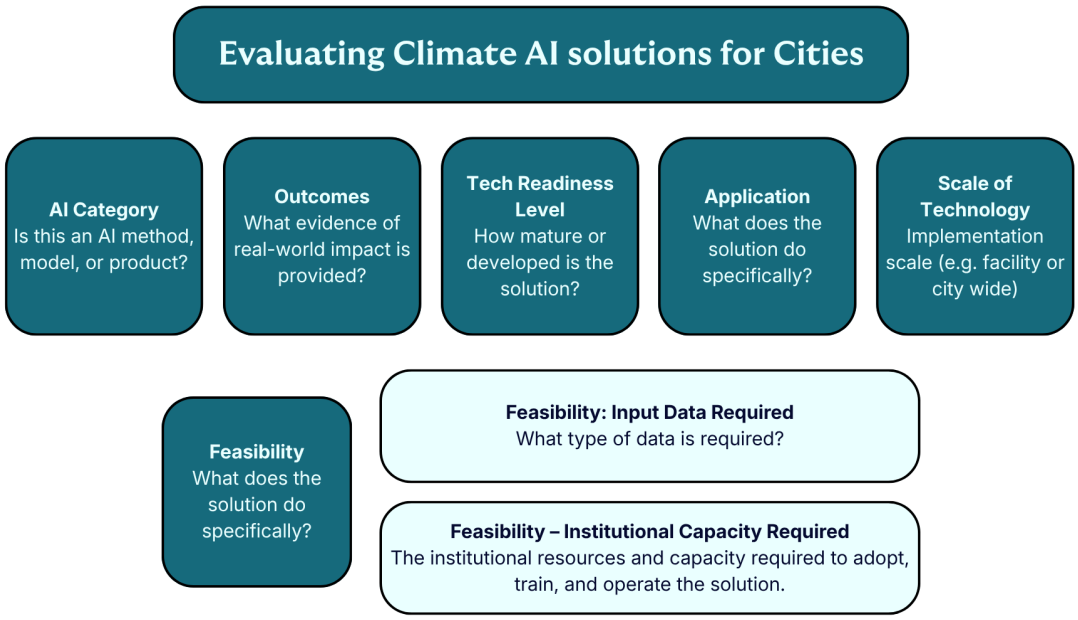


Figure 4. Key variables for evaluating Climate AI solutions for cities.

Framework for Cities Climate AI Solutions Landscape

To support more systematic comparison across Climate AI solutions, this report develops a practical evaluation framework (Table 1) for assessing solutions in a consistent and decision-relevant manner. The framework is designed to help cities understand how a given solution can be classified according to its technical form, expected outputs and outcomes, level of deployment readiness, potential scale of implementation, and the input data and institutional capacity required for effective adoption. As shown in Fig. 4, these dimensions are intended to move assessment beyond broad claims about innovation and toward a clearer understanding of feasibility, maturity, and fit for urban climate action. The framework contains 15 variables in total, the majority of which are categorical to enable comparison across solutions. Table 1 describes these variables in greater detail.

While the assessment framework is intended to be applicable across diverse cities and contexts, it draws on key environmental pillars from the Global Covenant of Mayors for Climate & Energy (GCoM), namely mitigation, adaptation, and energy access.

Table 1. Climate AI solutions framework

Variable	Description
Pillar	The main climate objective addressed by the solution. This variable is based on the three core pillars of the Global Covenant of Mayors for Climate & Energy – Mitigation, Adaptation, and Energy Access. • Mitigation: reduction of greenhouse gas emissions • Adaptation: adapting cities and communities to minimize the impacts of climate change • Energy Access: improving access to clean and affordable energy Note: a few solutions fall under multiple pillars.
Subcategory	A thematic area within each pillar that describes the specific sector or domain addressed by the solution. The subcategories identified include: (1) AI Chatbot, (2) AI Tutorial, (3) Air Quality Management, (4) Building Project Management/Climate Planning, (5) Carbon Impact Assessment, (6) Climate Forecasting, (7) Data Collection, (8) Disaster Prevention/Protection, (9) Electric Vehicle Management, (10) Emissions Management, (11) Energy Consumption Tracking, (12) Energy Saving Verification, (13) Environmental Impact Monitoring, (14) Forest Management, (15) Forestry Management, (16) Forests/Carbon Markets, (17) Grid Infrastructure and Integration, (18) Heating/Cooling, (19) Heating/Cooling/Energy Efficiency, (20) Infrastructure Management, (21) Measuring/Quantifying Carbon Footprint, (22) Methane Detection, (23) Policy Analysis, (24) Preparedness, (25) Prevention, (26) Renewable Power Generation, (27) Transportation Efficiency, (28) User Productivity for Energy Access, (29) Waste Management, (30) Weather Prediction, and (31) Wildlife Protection.
Name of Developer/ Product	Name of the organization, firm, or solution provider offering the Climate AI product or service.
AI Category	The solution's stage of development categorized into one of the following three types: • AI Method: Solutions at this stage indicate that they provide foundational AI algorithms, such as machine learning (ML), deep learning (DL), and natural language processing (NLP) adapted to a specific climate topic. This solution generally requires greater technical capacity or know-how for effective application due to the need for direct implementation and user data for training and use. • AI Model/Package: Solutions at this stage combine multiple methods and have been trained on a set of data to recognize certain patterns and generate predictions or outputs. They can also include locally hosted interfaces and open algorithms to address specific questions and querying data sources. While more easily deployed than a base "AI Method," these solutions typically still require some capacity, technical know-how, as well as specific input data to effectively implement and utilize.

Variable	Description
AI Category Cont.	• AI Product: Solutions at this stage include cases of fully developed technology or software that integrates multiple AI Methods and Models to deliver outputs, with accessible user interfaces, maintenance and custom support. An "AI Product" is considered an "off-the-shelf" solution that requires relatively less technical capacity for a city to implement since a solution provider may provide support for implementation or data to be used with the product.
AI Descriptor	A brief, qualitative explanation of the solution and how it is used in a practical manner (e.g., a dashboard that provides real-time insights based on predictive analytics).
Application	A short description of the solution's impact and how it is specifically applied for a context or use-case (e.g. "Energy Demand Forecasting").
Outcomes/Results	Description of solution's real-world performance and success, such as successful deployments in other cities, contracts/grants secured, publicly available performance metrics/ data, or measurable impacts.
Open Source	Indicates whether the solution is considered "open source" (source code available in open and free repository) – Yes/No.
Technology Readiness Level	Each solution is classified into one of the following categories describing market and deployment maturity: • Pilot and Development: The technology is still being researched or piloted. The provider might not have a product readily available for full-scale deployment. • Early Adoption: The technology has been adopted by a few users or cities already. The solution provider is likely able to deploy the solution for new users/cities though the provider might still be fine-tuning the solution. • Broadly Available: The technology is fully developed and available commercially for purchase and implementation.
Scale of Technology	The implementation scale of the solution – Facility, City, Regional, or Global.
GCoM Journey	Indicates which of the stages in a city's journey – based on GCoM's City Journey – the solution is most relevant to. GCoM specifies 8 stages of a city's journey in urban climate action, which are: • Commit – a pledge to take climate action • Assess – understanding and quantifying city's greenhouse gas inventory. • Set goals and targets – which should be at least as ambitious as their country's Nationally Determined Contributions under the United Nations Framework Convention on Climate Change (UNFCCC). • Develop action plan – for mitigation and adaptation

Variable	Description
GCoM Journey Cont.	• Implement – adopt solutions • Monitor and report – sharing standard and consistent data for transparency • Validate – GCoM verifies progress for the global community • Update – refreshing plans with evidence-driven policy and action recommendations For instance, if a solution helps a city to measure and quantify its emissions, it would be indicated as "Assess," while a solution that supports the strategizing and drafting of climate strategies would be indicated as "Develop action plan". Please note that this indicator is not mutually exclusive since the same solution can potentially be relevant for multiple stages.
Feasibility – Input Data Required	The data required by the solution provider for effective implementation and use (e.g., city sensor data, open access satellite data, etc.). This information is gauged from the solution provider's website but cities should discuss their data availability and limitations with providers to better evaluate the feasibility and potential impact of implementation. If "no data required" is indicated, the provider is likely able to source data themselves or via other means such as leveraging free data sources or paid services.
Feasibility – Institutional Capacity Required	The institutional resources and capacity required to adopt, train, and operate the solution (e.g. technical know-how, staff capacity, etc.). For ease of identification this is categorized into 3 levels: • "Low institutional capacity required" indicates that a solution can be adopted with existing city infrastructure and resources without requiring extensive new equipment (e.g. sensors) or specialized staff for deployment and maintenance. • "Medium institutional capacity required" indicates that the city may need to procure some additional equipment (e.g. sensors) or hire/train staff to implement, operate, and maintain the solution. • "High institutional capacity required" indicates that the solution requires advanced institutional readiness. Cities might require extensive sensor networks, technical capabilities, data collection means and processes, and trained staff who can coordinate with solution providers and work with the AI technology from the deployment stage to long-term maintenance.
Company / Provider website	Link to the website of the solution provider.
Supporting references	References such as news articles or academic research papers about the solution provider.

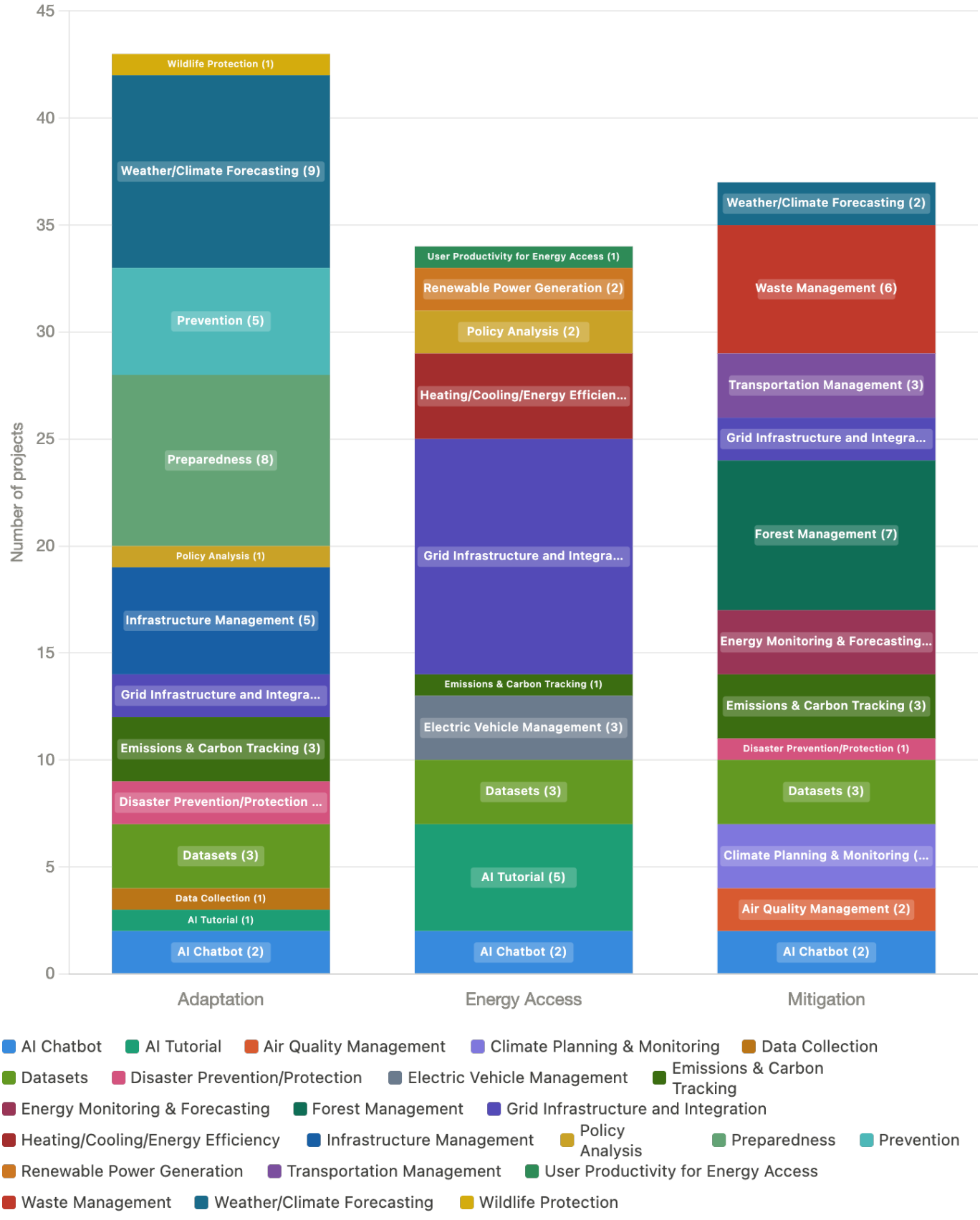


Figure 5. Overview of pillar and subcategory breakdown.

Climate AI Solutions Landscape Database

To help cities better understand the current landscape of Climate AI solutions, this report includes a database of available AI solutions through a combination of literature review, desktop research, and outreach to Climate AI providers. We identified 100 unique Climate AI solutions from industry reports, news websites, company websites, investment databases, and academic publications. This database is not meant to be a comprehensive survey of the entire solution landscape, but rather, a curated selection of solutions for which sufficient publicly available information existed to enable analysis using the framework developed in this report. These solutions reflect a range of open source tools that include ML or deep learning models, tutorials, datasets that help cities prototype or build their own solutions, and proprietary tools that include vendor platforms or software. The database reflects a rough balance of the two solution types, with open-source entries being mostly model or method-oriented, and non open-source solutions being mostly AI products that are primarily operational climate-tech products that help cities with a specific task, such as flood monitoring. The main difference is that open-source tools typically require more technical and institutional capacity to operate, while vendor products often reduce city data and technical burdens by bundling data collection and analytics alongside support. The report's aim is not to promote one solution type over the other; rather the goal is to survey the existing landscape of solutions and to provide a framework for cities to evaluate what solution type might be best for them, considering limitations and trade-offs associated with each approach.

Fig. 5 shows that the Climate AI solutions in our database are distributed unevenly across the three pillars: adaptation contains the largest number of AI solutions (43), followed by mitigation (37) and energy access (34), although some solutions fall under multiple pillars. The adaptation pillar is mostly dominated by hazard-related applications, with weather prediction and climate forecasting (9 total solutions, represented as "weather/climate forecasting" in Figure 5), preparedness (8), and prevention (5) accounting for a substantial share of the projects. This result suggests that within adaptation AI is primarily being used to improve risk detection, early warning, and anticipatory planning rather than post-event response measures.

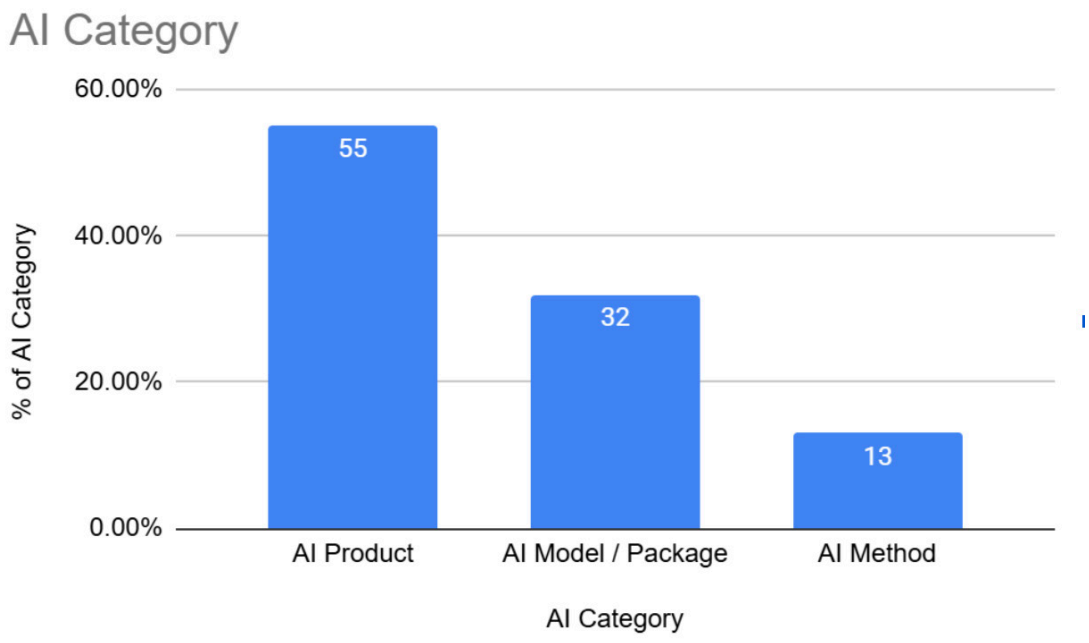


Figure 6. AI Category Breakdown.

In contrast, energy access is more concentrated in a smaller number of infrastructure and system-oriented categories. The largest subcategory is grid infrastructure and integration (11), with a smaller cluster of applications such as AI tutorial (5), Data Collection (3), Electric Vehicle management (3), or Heating/Cooling/Energy Efficiency (3). This distribution suggests that energy access AI applications are currently centered less on end-user services and more on enabling system coordination and grid management.

The mitigation pillar shows a distinct profile, with the strongest concentration in sector-specific operational uses. Here, forest management (7) and waste management (6) stand out as the largest categories, followed by a second tier of applications in transportation (3), and emissions/carbon tracking (3), energy monitoring and forecasting (3), and climate planning and monitoring (3).

Across all three pillars, we also found cross-cutting AI approaches, including chatbots, tutorials, and datasets that use AI to facilitate learning and management for cities. In our database, 13% of solutions are classified as AI Methods, 32% as AI Models, and 55% as AI Products (see Fig. 6). Most of the catalogued solutions fall into the "AI product" category, which are solutions that cities can adopt more easily than an AI Method or Model. This is as AI methods and models are generally not "off-the-shelf" solutions since they typically require greater technical expertise, more specialized data, and stronger institutional capacity to operate.

In the database, 33% of solutions are in a "Pilot Stage," 22% in an "Early Adoption" stage, and 45% are classified as "Broadly Available." (Fig. 7). While this database is not meant as a comprehensive study of the entire market of available AI solutions, these figures highlight how the Climate AI solutions landscape is maturing and how a substantial share of solutions have yet to move beyond pilot deployment. Given the nascency of AI pilots and the fact that the majority of available solutions fall into either the pilot or early adoption phases, cities need to carefully scrutinize vendor claims regarding the performance, impact, and scalability of proposed solutions.

In both of the "AI Category" and "Technology Readiness Level" variables, we observe that only 31 solutions are AI

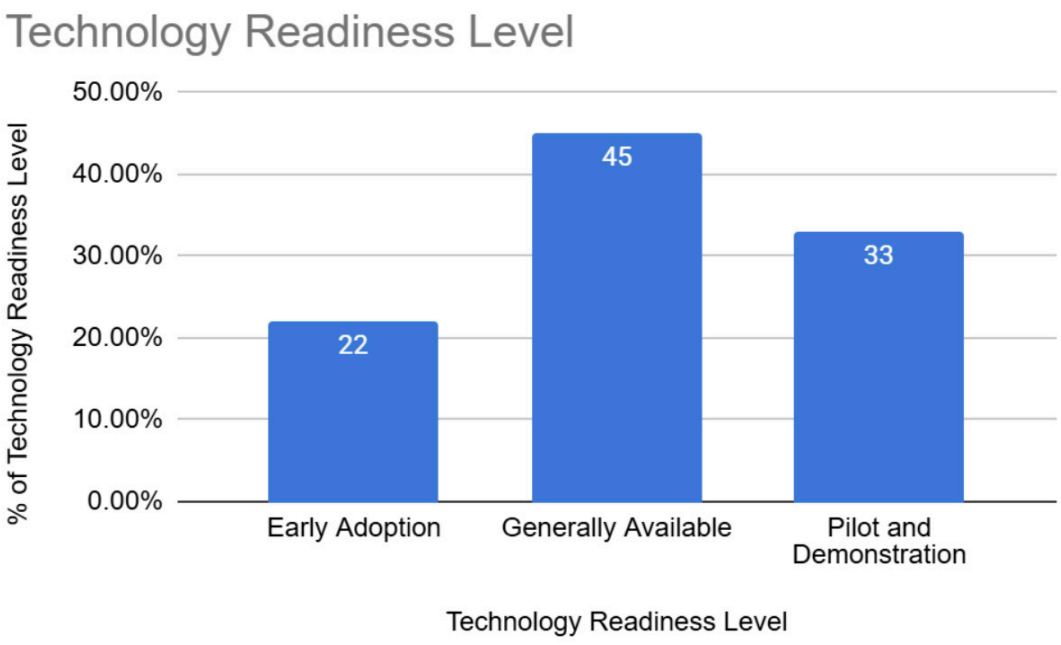


Figure 7. Technology Readiness Level Breakdown.

Products that have moved past the pilot stages, indicating that from a supply perspective, the Climate AI industry still has room for growth. It is also worth noting that most identified solutions are built on more established approaches, such as machine learning and deep learning with only 3 solutions incorporating GenAI as part of their core methodology. As the GenAI space continues to develop, particularly in multi-modal and agentic applications, more Climate AI solutions powered by GenAI are likely to emerge, potentially raising the complexity of implementation, cost, and energy consumption.

Cost - a critical but missing consideration in assessment of Climate AI solutions

While the cost to implement a Climate AI solution is a critical consideration for cities, this information is rarely disclosed publicly and therefore, not available in our database. Evidence suggests that costs vary widely depending on factors such as the type of solution, scale of deployment, level of customization required, data inputs needed, and whether the product requires new equipment (i.e., sensors) or proprietary datasets. For example, the cost of environmental sensors to support real-time monitoring for AI applications, digital twins, or predictive modeling could represent a substantial cost for cities even if they are considered "low-cost." C40 Cities for Climate Leadership estimates that deploying a network for air pollution monitors costs between $15,000 and $100,000 USD in addition to "highly-trained technical staff to operate and maintain."[45] Another peer-reviewed academic study of flood sensor networks in the U.S. for flood risk mitigation finds that annual operation costs range between $55,000 and $1.5 million USD, with yearly maintenance costs ranging between $25,000 and $602,000 USD.[46] While low-cost sensors are cheaper to deploy, research has shown that there are limitations to using these, such as limited battery life, the need for manual data syncing in the absence of transmitters, sensor drift, and variance in the quality of data collected due to installation or interaction of sensors with surrounding ambient environments.[47] In some cases, the use of low-cost sensors is limited to one-off citizen science or community engagement campaigns, such as the HeatWatch program of the U.S. National Oceanic and Atmospheric Administration (NOAA), which provided cities with a one-time low-cost heat mapping campaign to collect high resolution air temperature data.[48] The data collected was then combined with remote sensing data in a machine learning model to estimate high-resolution air temperature data for cities,[49] including Raleigh, North Carolina, to identify priority areas for urban heat mitigation measures.[50]

Implementation costs vary considerably and are shaped by factors such as city size, geographic context, data availability, model complexity, customization needs, and whether new hardware (i.e., sensors) or additional cloud computing infrastructure are required. Beyond upfront costs, many solutions also have subscription or licensing costs that cities should factor into their budgeting. For example, the cost of Jupiter Intelligence's climate risk platform ranges from $25,000 to multi-million dollar contracts depending on scope and scale.[51]

Since pricing information was not publicly provided by most solution providers in our database, we reached out to several of them to request cost information. We found that pricing structures typically vary widely across solution providers, ranging from fixed-cost models based on city size and solution complexity, such as Software as a Service (SaaS) models

45 C40 Cities Climate Leadership Group. (2022). How resource-constrained cities can assess local air pollution. C40 Knowledge Hub. www.c40knowledgehub.org/s/article/How-resource-constrained-cities-can-assess-local-air-pollution?language=en_US.

46 Adesina, M., Brake, N., Asli, H. (2025). A survey of flood warning sensor network operational and maintenance practices across the United States. Developments in the Built Environment, 23, 100689. https://doi.org/10.1016/j.dibe.2025.100689.

47 Berk, S., Chakraborty, TC., and Hsu, A. (2025). Biases due to widespread use of low-cost sensors for urban heat stress assessments. EarthArXiv. https://doi.org/10.31223/X5WQ8R.

48 National Integrated Heat Health Information System. (n.d.). Urban Heat Islands – Mapping Campaign Program. Heat.gov. https://heat.gov/urban-heat-islands-mapping-campaign-program/.

49 Shandas, V., Voelkel, J., Williams, J., and Hoffman, J. (2019). Integrating satellite and ground measurements for predicting locations of extreme urban heat. Climate, 7(1), 5. https://doi.org/10.3390/cli7010005.

50 NC Resilience Exchange. (n.d.). Raleigh curbs urban heat islands through pavement rejuvenation. NC Resilience Exchange. https://www.resilienceexchange.nc.gov/identify-actions/success-stories/raleigh-curbs-urban-heat.

51 Clancy, H. (2022). The climate risk analytics software scene is expanding. Trellis. https://trellis.net/article/climate-risk-analytics-software-scene-expanding/.

that include access to proprietary data or hybrid approaches or a one-time fixed cost for sensor installation alongside an ongoing SaaS fee for platform access and usage. Even for open-source tools that do not charge any upfront fees, these tools could depend on cloud services for computing power that incur usage-based costs for users. For instance, GenAI solutions also often require ongoing access to an LLM provider's Application Programming Interface (API) services, which represent 'hidden' costs that cities must account for. While both open-source solutions and locally hosted ones do not incur subscriptions or general fees, these solutions require some investment in capacity and computing hardware.

It is well established that cities remain significantly underfunded for climate action – the 2024 State of Cities Climate Finance report indicates that annual urban climate finance must increase more than fivefold to attain a 1.5°C climate pathway by 2030. In this context, while Climate AI solutions may help cities improve efficiency and accelerate progress toward climate goals, they are not deployed in a resource vacuum.[52] Cities therefore require as much transparency as possible regarding both the explicit and implicit costs associated with the full lifecycle of a solution to seek financing before committing to any deployment. Although examples of Climate AI-specific public procurement arrangements remain limited, the growing maturity of these solutions will likely result in cities adopting procurement structures similar to those used for digital technologies and services such as Service Level Agreements (SLAs) or Pay-for-Performance (P4P) contracts. Finally, although a detailed discussion of global financing mechanisms falls beyond the scope of this report, an analysis by the UNDP warns that AI can widen gaps between nations, setting the stage for the "Next Great Divergence." UNDP explains that high-income countries are already "far better positioned" to adopt and benefit from AI, leading to a capability gap and a concentration of innovation at the top. Expanding technical assistance and financing for resource-constrained cities will be critical to ensuring that the benefits of Climate AI are broadly shared rather than concentrated among cities with more resources.[53]

52 Press-Williams, J. ,et al. (2024). 2024 State of Cities Climate Finance. Climate Policy Initiative. https://www.climatepolicyinitiative.org/publication/2024-state-of-cities-climate-finance/.

53 Schellekens, P. & Muthukrishna, M. (2026). The Next Great Divergence: How AI Could Split the World Again If We Don't Intervene. United Nations Development Programme. https://www.undp.org/asia-pacific/blog/next-great-divergence-how-ai-could-split-world-again-if-we-dont-intervene.

Evaluating the Foundations for Climate AI Adoption: Balancing Data Availability and Institutional Capacity

This section outlines some key considerations for cities when evaluating Climate AI solutions and engaging with solution providers.

What should cities consider before evaluating potential AI solutions?

Cities should first consider their **(1) data availability** to implement a particular Climate AI solution and their **(2) institutional capacity** to determine which Climate AI solutions they can feasibly and effectively adopt.

According to a 2025 report by the Organisation for Economic Co-operation and Development (OECD) on governing with AI, the most common challenge in the adoption of AI for governments is the "skills gap" among their workforce, which was cited as an especially significant challenge for subnational governments. Other significant challenges include the general lack of accessible, high-quality data as well as the limited ability of city staff and departments to share usable data across different jurisdictions and levels of government.[54] Long approval processes, rules that prevent data sharing, inadequate technical or policy protocols, and lack of interoperability across IT systems and data formats are also common bottlenecks. In terms of the "skills gap," a lack of "policy analytical capacity" points to a government's inability to analyze

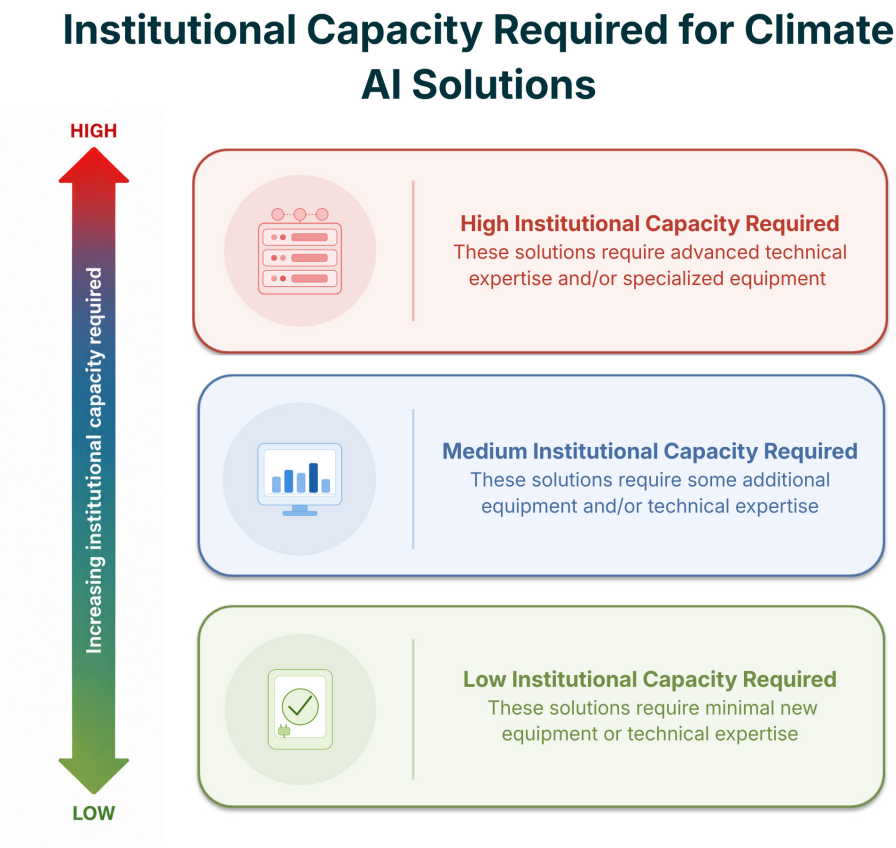


Figure 8. Institutional Capacity Requirements for AI Solutions.

54 OECD. (2025). Governing with Artificial Intelligence: The State of Play and Way Forward in Core Government Functions. OECD Publishing, Paris. https://doi.org/10.1787/795de142-en.

information, apply research methods, and use advanced modeling techniques for city planning and management.[55] The issue of "skills gaps" is especially crucial as it can exacerbate other risks and challenges, leading to "poor outcomes, overestimation and misplaced trust in AI capabilities and systems, and inadvertent misuse and general non-compliance with laws and other rules,"[56] particularly as more GenAI and Agentic AI tools become more widespread and shift decision-making and accountability away from human judgment.

In our solution database, we classified solutions according to the level of institutional capacity required, mainly "low," "medium," and "high."[57]

- **Low institutional capacity**: These solutions require minimal new equipment or technical expertise for their deployment making them relatively easier to implement. An example is "Sipremo" which uses AI to monitor, predict, and warn users about likely extreme climate events. Cities can adopt this tool for their climate adaptation and risk management needs without needing staff with specialized technical training for implementation and regular usage.
- **Medium institutional capacity**: These solutions require some additional equipment and/or technical expertise for their deployment and maintenance, but not at an extensive level. For instance, Vianova provides AI-powered analytics to help cities understand movement and traffic patterns. Traffic data collected by the city can be opted into Vianova's dashboard for further data visualization and analysis, meaning that some technical expertise is required from city staff to connect data and make use of insights.
- **High institutional capacity**: These solutions require advanced technical expertise and/or specialized equipment for their deployment, operation and usage. An example is Catastrophe AI for Climate Risk Modeling (CATIA), an open source tool that can help cities identify multi-peril climate risk. The tool, while available for free and powered by some open source data, requires considerable effort and resources to deploy and operationalize.

It is worth noting that "low capacity" here assumes a baseline level of infrastructure such as reliable internet connectivity and electricity, access to computers, or digital capabilities that some cities, particularly in lower-income contexts, may not yet possess. For these cities, foundational investments in infrastructure may need to precede AI adoption entirely.

In our database, 23% of Climate AI solutions are estimated to require low institutional capacity for deployment, 59% require medium capacity, and 18% require high capacity. While many of the low institutional capacity solutions are AI products, it's worth considering that the data required by the solutions and the interoperability across municipal functions determines how much capacity the city needs for their effective deployment. Thus, some Climate AI products that rely primarily on third-party data and require limited coordination, such as heat-monitoring or weather forecasting applications, might be considered as requiring lower-institutional capacity compared to other AI products, such as energy or traffic management, that require the collection of new data or coordination across multiple domains and teams. In terms of data requirements, we estimate that 36% of solutions in our database actively help cities collect data, 36% require cities to provide their own existing data, and 28% draw on external datasets, meaning cities do not need to extensively source and clean data for many of these solutions. It is important to note that cities might not need complete or "perfect" datasets before embarking on AI pilots or projects. In many cases, "good enough" data is sufficient for Climate AI solutions to produce meaningful insights and outcomes particularly when the use case is not high-stakes. While cities might feel a lack

55 Howlett, M. (2009). Policy analytical capacity and evidence-based policy-making: Lessons from Canada. Canadian Public Administration.

56 OECD. (2025). Governing with Artificial Intelligence: The State of Play and Way Forward in Core Government Functions. OECD Publishing, Paris. https://doi.org/10.1787/795de142-en.

57 In the solution database, these classifications are based on our internal estimates based on publicly available data about the solution provider. Cities can still consult with providers directly to determine whether implementation is feasible given their context.

Table 2. Key internal considerations for cities evaluating Climate AI solutions

What is the benefit of implementing an AI solution as opposed to business-as-usual? Can the city adjust its decision making process to realize the benefits of AI?	Given the hype around AI, cities need to be clear about what an AI solution actually offers over existing approaches and whether that added value is meaningful for their intended use case. At the same time, the level of detail generated by some AI solutions can become a liability if city decision-making processes are not equipped to act on that information – a risk sometimes referred to as "analysis paralysis."
Do city staff have the technical know-how and support from leadership to effectively adopt and manage Climate AI solutions?	While many cities are exploring the adoption of AI, only a very small minority has invested in building staff capacities or set policies and guidelines to govern AI use.[58] If a city does not currently have high technical know-how, it should consider "plug-and-use" Climate AI solutions that require less expert input/management in the short-run while building staff capacity for the future. Cities like San Francisco have previously upskilled city staff by training technical capabilities,[59] and other cities have turned to local universities to develop bespoke solutions for local contexts.[60]
Does the Climate AI solution have synergetic effects with other use-cases?	Consider prioritizing solutions that have knock-on effects with other priority domains for the city if cross-departmental data and coordination is feasible. For example, a Climate AI solution to alleviate traffic would reduce emissions emitted by vehicles while reducing lost economic productivity which may be especially valuable if a city is concerned about poor traffic and air quality.
What special conditions does the city face?	Consider whether the Climate AI solution aligns with local knowledge/ data sources, needs, and local priorities. This is especially important for climate adaptation and energy access solutions since cities face different climatic conditions, risks, and legislation.
Are there other peers to learn from?	There are several city networks such as Bloomberg Cities Idea Exchange that facilitate cities in learning from each other. Cities can consider tapping on such networks or existing partnerships/contacts for knowledge sharing and capacity building, especially with peers that share similar urban, environmental, cultural, and legal infrastructures. This applies for both selecting specific solution providers as well as the development of institutional capacity and guidelines/ policies.

58 City AI Connect. (2023). State of Cities: Generative AI in Local Governments. Johns Hopkins University. https://cityaiconnect.jhu.edu/pdfs/Final-Gen-AI-In-Cities-Report_10.18.2023.pdf.

59 SF.Gov. (2025). Mayor Lurie Brings AI Technology to San Francisco Government, Cementing City as Global AI Leader. SF. Gov. https://www.sf.gov/news-mayor-lurie-brings-ai-technology-to-san-francisco-government-cementing-city-as-global-ai-leader.

60 Orenstein, N. et al. (2025). Oakland is quietly incorporating AI into city work. The Oaklandside. https://oaklandside.org/2025/10/17/oakland-quietly-incorporating-ai-into-city-work/

What are the city's procurement and budgetary structures?	Traditional procurement processes and budgetary items/lines are often designed for well-defined, established services which might be a barrier to entry for emerging Climate AI solution providers. Consider assessing whether municipal/city/state procurement and budgetary systems are flexible enough to accommodate emerging solution providers and performance-based contracts, and if any adaptation or restructuring would facilitate adoption. Simultaneously, are there procurement provisions that can be included that require AI providers to be transparent about their energy, water, and climate impacts? Beyond the initial purchase cost, cities should also evaluate the full lifecycle cost of implementation, such as the cost of new equipment, potential future price changes, system integration, staff training, and more. Understanding these long-term financial costs alongside potential funding sources can help cities determine whether a solution is financially aligned with their broader climate goals and their overall financial capacity.
What are the climate KPIs and pledges undertaken by the city?	What are the binding or important climate pledges that the city undertook? What KPIs are important on a city, regional, or national level that a Climate AI solution can effectively address, and can this solution complement existing strategies and practices? Understanding a solution's energy consumption, water use, and associated emissions can help ensure that it supports, rather than undermines, the city's broader climate goals. Cities need to ensure that the adoption of Climate AI solutions will help deliver meaningful outcomes that are aligned with their environmental commitments.
What AI governance frameworks, data regulations, and municipal policies regulate the use of AI in the city?	Consider the regulatory frameworks and policies shaping the adoption of AI solutions for a city. What compliance, transparency, and accountability requirements must solution providers satisfy, and does the city have the capacity to effectively track, govern, and oversee these digital technologies? Cities need to consider and discuss data ownership, sharing agreements, safety, transparency, and accountability when sharing data with solution providers including failsafe mechanisms and end of use considerations. Regardless of the type of data used, cities should remember that accountability for the data stewardship and decisions from the use of Climate AI solutions cannot be outsourced or delegated.

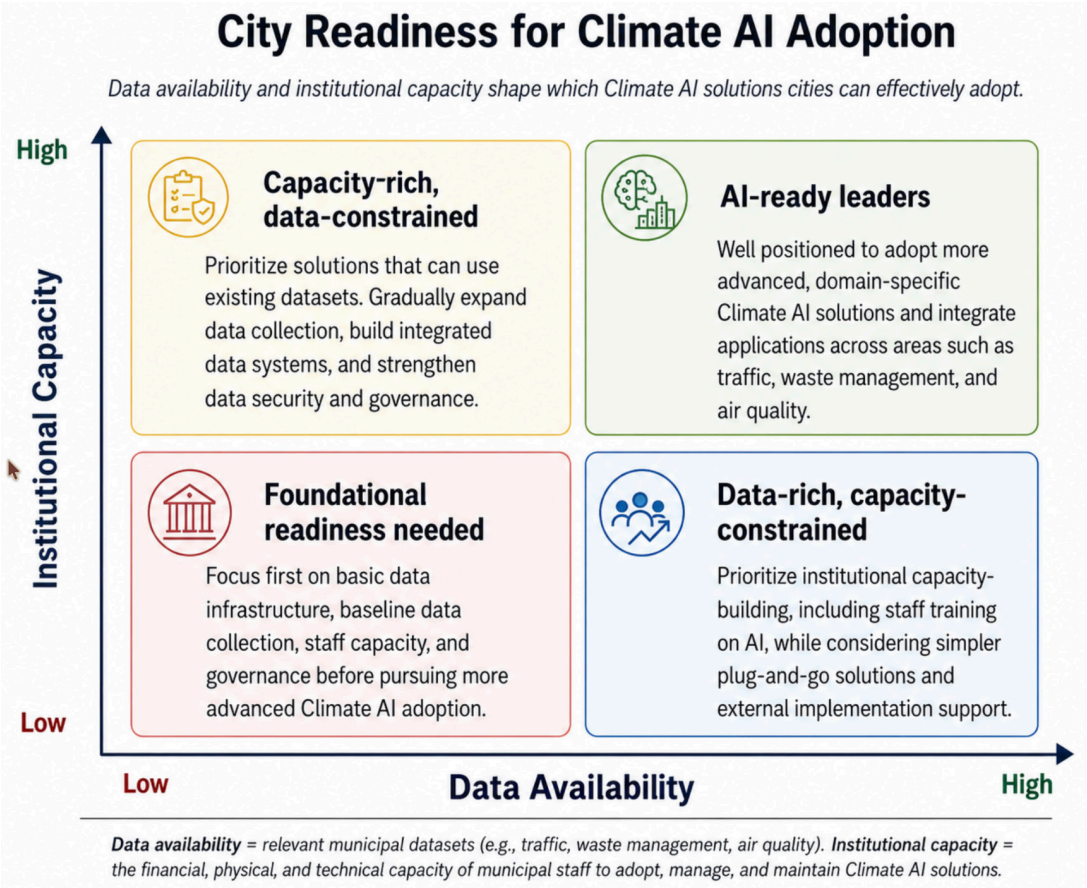


Figure 9. Framework demonstrating priorities for cities given institutional capacity and data availability.

of confidence in the completeness, quality, or granularity of their data, data is seldom flawless in organizational settings and the pursuit of 'perfect data' can become a barrier to action. This is especially true for lower-stakes applications where technical benefits can be substantial, occasional errors or gaps have limited consequences, and a city can reasonably start with existing data. However, in high-stakes applications where poor data quality or misinformed outputs can result in serious consequences, data inputs need to be examined more rigorously alongside the implementation of safeguards. In these high-stakes applications, any autonomous system should still require human review and decision-making.

At the same time, messy or unstructured data does not have to be a significant barrier provided that it is paired with appropriate safeguards and/or it is the only viable option. PetaBencana provides a compelling example for this argument. Its engineers relied on 'messy,' unstructured social media data because government capacity and resources are insufficient to effectively detect, monitor, and respond to natural disasters outside of major urban areas in Indonesia. Instead of waiting for this capacity to be built over the long-run, PetaBencana was designed to independently scrape, clean, and gain insights from publicly available social media data, reducing the burden on local governments while relying on additional human verification processes to improve disaster response for these communities. This demonstrates that messy data can still power impactful tools in resource-constrained, high-stakes contexts, though implementation still needs to be balanced with additional validation processes.

As a result, even if a city has lower institutional capacity as well as limited or messy data, they could still feasibly adopt some AI solutions, demonstrating how Climate AI can sometimes help address climate issues for cities that are still scaling

their institutional capacity by providing access to previously curated data or establishing systems to collect, clean, and analyze messy or unstructured data. Lastly, Climate AI solutions can also be fine-tuned as more or higher-quality data becomes available over time and cities strengthen their institutional capacity.

The framework in Fig. 9 illustrates how a city's level of data availability and institutional capacity shapes their readiness for the adoption of Climate AI solutions. The framework presents four broad readiness categories across two dimensions: (1) the availability and quality of relevant data and (2) the institutional capacity required to implement and manage Climate AI solutions.

- **Cities with both strong institutional capacity and data availability** are usually well positioned to adopt more advanced and domain-specific Climate AI applications, especially across multiple municipal functions. Cities in this category have the ability to experiment with more innovative or customized solutions.
- **Cities with strong institutional capacity but limited data** may need to prioritize solutions that utilize existing datasets while gradually improving data collection for other domains, building more integrated data management systems, and/or enhancing data security and policies.
- **Cities with more data but limited institutional capacity** may wish to prioritize institutional capacity-building (such as training staff on using AI) while considering simpler 'plug-and-use' solutions.
- **Cities with limited institutional capacity and limited data availability** may first need to focus on building stronger foundations by developing infrastructure, their workforce, as well as their data collection and management capabilities. These cities might need to tap into free or open-source solutions that do not require heavy expertise.

Box 3. Key considerations when discussing solution adoption with potential providers

After identifying a potential solution, cities can use the following questions to guide discussions with a solution provider:

- Implementation:
  - » What technical and non-technical requirements are needed from the city for successful implementation?
  - » What support can the solution provider provide to help the city implement and manage the AI solution effectively?
  - » Will the solution be interoperable if the city switches to a new provider or develops in-house capabilities in future?
- Results:
  - » What other success stories/evidence/metrics can the vendor share that is not publicly available? Are those cases implemented in cities in similar contexts or challenges?
  - » Given the city's resources, context, institutional capacity, and data, what would be the estimated outcomes or impacts?
- Pilot testing:
  - » Do they allow for pilot runs or proof-of-concept testing before full-scale deployment?
  - » Will pilot results accurately reflect full-scale deployment?
- Data governance:
  - » What are the governance and ownership clauses, especially when dealing with municipal/governmental data?
  - » Is data portable (e.g. if transferring to a new vendor in future)?
  - » Who owns the right to the model trained on city data?
- Compliance:
  - » How will the vendor comply with local cybersecurity, data privacy, and ethical standards and regulations?
- Scalability:
  - » Can the results of the solution be easily explainable and thus, scaled or adapted for other municipalities, cities, or use-cases?
  - » Are there any data interoperability challenges?
- Cost:
  - » What are the long-term costs (e.g. maintenance, updating models, etc.) beyond the initial start-up cost and contract period?
  - » Are there any cost structures that can be structured based on the impact or performance of the solution?
- ESG/Energy Disclosure:
  - » Do they disclose energy use, model efficiency, and their Environmental, Social, Governance (ESG) impacts?
  - » Is the AI model deployed locally on municipal computers or servers or hosted on external infrastructure?

- Risks:
  - » What risks should cities anticipate given the Climate AI's underlying technology or intended outputs?

Ultimately, while data availability and institutional capacity are important starting points, successful Climate AI adoption also depends on a wider set of internal conditions such as staff expertise, leadership support, and procurement flexibility. The questions in Table 2 are designed to help cities assess their readiness across these dimensions. The underlying premise here is that the success of any Climate AI solution depends not only on the quality and requirements of the solution itself, but also on the city's internal operational context.

Once cities have assessed their overall readiness level, our database can serve as a starting point for identifying AI solutions relevant to their use case before exploring in more detail those that also align with their readiness level. Cities can also use Box 3 to guide discussions with solution providers during the evaluation and procurement process.

Additionally, the database includes additional variables to help identify solutions of particular interest, such as whether a solution is "open source" and the geographical scale it is designed to support (i.e. at a facility or city-wide level). Generally, cities classified as "AI-Ready Leaders" are likely to have access to a wider range of solutions given that they possess the technical capacity and infrastructure needed to deploy AI models and packages that require more advanced skills and equipment.

What are risks in deployment of Climate AI solutions?

Climate AI solutions presents important opportunities for cities though it is important to note that these tools are not risk-free. This section examines the main risks and implementation risks that cities should assess when considering Climate AI solutions.

1. **Environmental impacts of AI.** AI solutions depend on computing infrastructure such as cloud platforms, data centers, and hardware that require substantial resources, including electricity and water. Cities adopting AI should evaluate whether the expected climate and environmental benefits of a solution outweigh the resources required to train and operate it, particularly for tools that involve intensive training of large models, frequent inference, or locally-deployed computing infrastructure. Alternatively, cities should ask the Climate AI solution developer what considerations, guardrails, and audit disclosures they have in place to ensure that environmental impacts are minimized in both the design and implementation.

    - **Energy Impacts**: A 2025 study estimated that aggregated across the US economy, AI adoption could lead to an "additional 28 petajoules of energy use and 896 kilotonnes of CO_2 emissions annually," which would comprise 0.03% of annual national energy use and 0.02% of annual CO_2 emissions in the U.S.[61] While these figures may appear modest at the national scale, the energy implications can be significant as AI adoption expands, particularly with the growing use of agentic and generative AI tools which typically consume substantially more energy.
    - **Data Centers**: Where AI computation is performed can substantially influence the environmental impacts of AI. Data centers are among the fastest-growing sources of electricity demand globally while their water use, grid impacts, and other negative externalities have become increasingly contentious at the local level.[62] Cloud-based AI solutions often rely on data centers located far from the cities using them – sometimes in another state or even country – meaning that many of the associated environmental costs are effectively externalized.

    For cities in the Global South or in regions with strained energy infrastructure that have committed to build and host new data centers, the implications can be even more severe. Local data centers may increase demand on grids already under pressure with knock-on effects for energy access and affordability. While cities, municipal departments, and their staff might not always have leverage over whether a Climate AI Solution is hosted locally, if possible, they can instill environmental policy that governs the construction and management of data centers within their border.

2. **Biased Data**. AI systems, especially GenAI and Agentic AI, detect and replicate patterns in data, including biases and omission. Biased or incomplete datasets may lead to biased outputs, reinforcing existing inequalities.

    In urban climate contexts, the communities most exposed to climate hazards are often the least represented (or misrepresented) in the datasets that AI systems are trained on. For example, weather hazard models and

61 Harding, A., and Moreno-Cruz, J. (2025). Watts and bots: the energy implications of AI adoption. Environmental Research Letters. https://iopscience.iop.org/article/10.1088/1748-9326/ae0e3b.

62 Walker, C., and Goldsmith, I. (2026). From Energy Use to Air Quality, the Many Ways Data Centers Affect US Communities. World Resource Institute. https://www.wri.org/insights/us-data-center-growth-impacts.

forecasting systems are trained on data that might primarily be from well-studied, higher-income neighborhoods, thus resulting in the systematic underestimation of risk in informal settlements or lower-income areas. Similarly, energy efficiency tools trained on data from cities in the Global North may perform poorly or produce misleading recommendations when applied to cities with very different contexts. The skewness present in training data can lead to what scholars have referred to as "algorithmic redlining," where AI systems reproduce or reinforce existing patterns of exclusion by directing resources or services away from communities whose risks are poorly captured in the underlying data.[63] Cities should ask vendors what data their solutions were trained on, if they have insights on the appropriateness of city's data, and how audits and failsafes for bias can be implemented.

3. **AI and Information Integrity Risks.** As AI becomes more widespread, the risk that information is misrepresented, distorted, or manipulated – whether deliberately or otherwise – is growing. Research from the Melbourne Centre for Cities distinguishes between disinformation, defined as "concerted fabrications that are deliberately misleading," and misinformation, or inaccurate information that is unintentionally held and/or shared.[64] Both phenomena can undermine the functioning of city administrations and elected bodies, with knock-on effects for governance, policymaking, and a city's capacity to address collective challenges such as climate change, public health, and social cohesion.[65]

   The magnitude of this risk is significant. According to the World Economic Forum's 2026 Global Risks Report, which surveyed over 1,300 global leaders and experts across academia, business, government, and civil society, "misinformation and disinformation" was ranked as the second most significant risk in the short-term (2026–2028) and the fourth biggest risk in the long-run (2026–2036).[66] The report notes that this risk was generally perceived as more pronounced in wealthier economies in the Global North, and one of the largest threats in both the short and long-run alongside "extreme weather events."

   The proliferation of generative AI is a key driver of this trend. GenAI enables the "rapid creation and targeted dissemination of synthetic content" including deepfakes, resulting in impacts such as political disinformation, propaganda, and scientific disinformation.[67] When intentionally misused, AI tools can erode trust in public institutions and deepen social divisions.

   However, even when unintended, AI tools can generate misinformation. A pressing example in GenAI and LLM-based tools is hallucination, or the production of outputs that are fluent, authoritative, and plausible-sounding but factually incorrect. In climate applications, this risk carries real consequences. For example, when general-purpose LLMs are used to summarize emissions regulations, interpret climate risk data, or generate policy recommendations, they may produce inaccurate outputs that sound credible, leading to serious implications for effective climate action.

   As such, cities considering the adoption of AI-based tools for information gathering and decision-making purposes should prioritize adopting domain-specific tools that have guardrails in place to prevent hallucination. An example developed by the authors of this report is ChatNetZero.ai, an LLM-based AI chatbot trained on selected

63 Hsu, A. (2025). From Pixels to Progress: Advancing Urban Environmental Justice in the AI Era. Oxford Intersections: AI in Society. https://doi.org/10.1093/9780198945215.003.0023.

64 Trijsburg, I, et al. (2024). Disinformation in the City: Response Playbook. The University of Melbourne. http://doi.org/10.26188/26866972.

65 Trijsburg, I, et al. (2024). Disinformation in the City: Response Playbook. The University of Melbourne. http://doi.org/10.26188/26866972.

66 World Economic Forum. (2026). The Global Risks Report 2026. WEF. https://reports.weforum.org/docs/WEF_Global_Risks_Report_2026.pdf .

67 López-Borrull, A., and Lopezosa, C. (2025). Mapping the Impact of Generative AI on Disinformation: Insights from a Scoping Review. Publications, 13(3), 33. https://doi.org/10.3390/publications13030033.

scientifically robust and peer-reviewed research for more accurate climate insights.

4. **Privacy.** Many Climate AI solutions, particularly those used for traffic management, urban heat mapping, waste monitoring, and so on, rely on the collection of real-time data in public areas.

   While this data is collected for legitimate and beneficial purposes, it raises significant concerns around privacy, data governance, and the potential for misuse and surveillance. Sensors, cameras, and other devices deployed in public areas can capture data about residents' movements, behaviors, and activities, often without their knowledge or consent.

   In addition, when Climate AI solutions involve third-party vendors, there are additional data risks and vulnerabilities. Cities adopting Climate AI solutions should ensure that data collection is governed by clear, transparent policies and that residents should have meaningful opportunities to understand, give feedback on, and engage with how their data is being used.

5. **Contingency.** As cities integrate Climate AI solutions into their workflows and critical infrastructure – including energy grids, flood warning systems, and traffic management software – the question of what happens when these systems fail, are compromised, or are taken offline becomes increasingly important. Unlike traditional infrastructure, failures in AI solutions can be difficult to detect and have cascading consequences that are hard to reverse. Failure could arise from cloud outages, energy shortages, or even cyberattacks from malicious actors. Cities should ensure that Climate AI solutions are accompanied by robust contingency planning, including clearly defined procedures for when AI systems are unavailable or compromised. This includes establishing protocols for detecting and responding to AI system failures as well as regular stress-testing and security audits of AI-dependent infrastructure. Cities should also ensure that contracts with solution providers clearly define protocols and responsibilities for system security, incident response, and liability.

6. **Governance.** As agentic AI and AI-based systems become more embedded in institutions and decision-making processes, the frequency of autonomous decisions being made without human oversight is rising, along with associated risks. Agentic AI systems can autonomously execute multi-step tasks, trigger actions, and interact with other systems with limited human intervention, raising questions about accountability, transparency, and the appropriate boundaries of automated decision-making in public governance. According to a MIT Sloan study, agentic AI adoption is spreading "faster than leaders can redesign processes, assign decision rights, or rethink workforce models."[68] The same study found that among organizations with extensive agentic AI use, over 70% of staff believed that AI enables their organizations to stand out, suggesting that competitive pressure may be driving adoption ahead of the development of appropriate guardrails, risk management policies, and governance frameworks.

   The consequences of inadequate governance can be significant. Organizations that fail to develop adequate frameworks for autonomous AI risk misaligned outputs and harms. While AI systems can make mistakes, the risk is that they do so in ways that are difficult to detect, challenge, or correct, particularly in contexts with limited human oversight or capacity. In the context of urban governance and climate action, where decisions about public spending, resource allocation, and climate action carry significant consequences for communities, cities need to establish

68 S. Ransbotham, D. Kiron, S. Khodabandeh, S. Iyer, and A. Das. (2025). The Emerging Agentic Enterprise: How Leaders Must Navigate a New Age of AI. MIT Sloan Management Review and Boston Consulting Group. https://sloanreview.mit.edu/projects/the-emerging-agentic-enterprise-how-leaders-must-navigate-a-new-age-of-ai/.

clear governance structures and policies before deploying more sophisticated AI solutions at scale, especially those that are agentic, integrated into critical infrastructure systems, or likely to have significant impacts on people and communities.

For cities without established AI governance frameworks, the Barcelona Centre for International Affairs has compiled several case studies on urban AI governance frameworks and policies, available here.[69]

While these are general risks that are also associated with the use of general AI, we have identified several other risks specific to the central pillars (mitigation, adaptation, and energy access) in our report.

- **Mitigation**: Many Climate AI solutions for climate mitigation often focus on optimizing energy and resource use. However, improvements in efficiency could lead to rebound effects, resulting in greater overall consumption that offsets emissions reductions.
- **Adaptation**: Many Climate AI solutions for adaptation include disaster/weather forecasting and prediction. If these systems are trained on incomplete, poor, or biased datasets, they may fail to accurately predict risks in certain areas.
- **Energy Access**: Grids and energy systems are among the most complex infrastructures cities manage, relying on continuous real-time balancing of supply and demand to maintain stability. Climate AI tools integrated into energy systems need to be carefully implemented and monitored to avoid errors that could disrupt energy reliability. A particular concern is that forecasting models that are trained on historical data may not be able to account for extreme weather events especially as the frequency and intensity of climate disasters intensify. If a predictive model fails to anticipate a sudden surge in energy demand during a heat wave or cold snap, grid operators may be unable to respond in time, increasing the risk of outages and human harm. In addition, AI systems trained on biased data could end up prioritizing high-demand or high-income areas, leading to greater inequalities in energy access.

7. **Dependence and Sovereignty.** Due to the outsourcing of data, computing resources, and data analysis to third-party providers, cities risk becoming dependent on systems and infrastructure they do not own or control. This dependence can affect long-term operational continuity especially if vendors increase pricing, discontinue services, restrict access to data, or fail to align with evolving public sector priorities.[70]

   For example, vendor lock-in can occur when switching from a provider becomes prohibitively costly or technically infeasible. This risk can arise from proprietary data formats and structures that hinder data migration, city-specific models that cannot be transferred or replicated elsewhere, opaque solutions that make it difficult for cities to understand or replicate them internally, and pricing structures where initial costs are deliberately kept low but increased substantially when a city becomes dependent on the solution. Once embedded into core infrastructure such as energy grid management or traffic control, switching providers can require significant retraining, implementation costs, and downtime, thus limiting a city's bargaining power and increasing its dependence on a single provider over time.

   Digital sovereignty relates to a city's ability to maintain jurisdictional authority over its own data and digital infrastructure. When computing facilities and data storage are hosted outside a city's jurisdiction, such as in another

69 D'oleo, A. (2024). Case studies of urban AI governance frameworks. CIDOB. https://www.cidob.org/en/publications/case-studies-urban-ai-governance-frameworks.

70 Nikolova, A. (2025). Challenges and risks in outsourcing government functions. Knowledge - International Journal, 73(1), 311–317. https://ojs.ikm.mk/index.php/kij/article/view/7917.

state or country, municipal data may become subject to foreign legal frameworks and risks. This can complicate compliance with local data protection laws and also pose a security concern if sensitive infrastructure data (e.g. energy grid, water systems, etc.) or personal data is hosted externally.[71]

Cities should ask vendors about contractual and technical safeguards to preserve their ability to switch providers while using the deployment as an opportunity to develop in-house capabilities for the future. This includes exit clauses that define the process, timeline, and cost of offboarding, clarity on ownership of models trained on municipal data, and the management protocols that reduce the risk of technical lock-in. Cities should aim to establish these safeguards at the contracting stage before a solution becomes intertwined with critical infrastructure.

When discussing potential adoption with a solution provider, cities can use these points for more targeted discussions about specific risks and safeguards.

71 Fleming, S. (2025). What is digital sovereignty and how are countries approaching it? World Economic Forum. https://www.weforum.org/stories/2025/01/europe-digital-sovereignty/.

Box 4. Why "open source" AI might not always be accessible

Open source technology or software refers to technologies that "anyone can inspect, modify, and enhance."[72] Examples of open-source software include Linux Operating System, media player VLC, or the office suite LibreOffice. While many open-source software are free to use, they are not always costless in practice as implementation, maintenance, and customization often require significant technical expertise and resources.

According to the Open Source Initiative, a non-profit that maintains the predominant standard for open-source software, traditional "open source software" must be distinguished from "open-source AI" since AI (and specifically machine learning models) blurs these boundaries with "data, configuration options, documentation and new artifacts, like weights and biases."[73]

According to the organization, open source AI is an AI system that allows users to:

- Use the system for any purpose and without having to ask for permission.
- Study how the system works and inspect its components.
- Modify the system for any purpose, including to change its output.
- Share the system for others to use with or without modifications, for any purpose.

Open-source AI is often considered a cost-effective and vendor-independent alternative to proprietary Climate AI solutions. Although open-source models can reduce dependence on a single vendor, they do not necessarily lower overall costs as implementation, customization, maintenance, and technical expertise can still require significant investment. AI systems, whether hosted locally on municipal servers or through a third-party cloud provider, require substantial computational resources. The total cost of a solution varies depending on whether the city decides to implement it using third-party resources or host it locally. For solutions deployed using third-party resources like some generative AI and agentic AI systems, costs are tied to token usage or subscriptions paid to the commercial model or cloud providers. For some locally hosted solutions, including open-source solutions, the city bears direct equipment and infrastructure costs such as computing (GPU/CPU), electricity, memory, storage and even technical staff to operate the solution though the city does not pay token or subscription fees to a model provider or cloud service. As a result, both approaches bear deployment costs that need to be clearly estimated in order to secure, plan, and distribute the funding required for implementation.

Open-source solutions are often viewed as a foundational component of Sovereign AI – or efforts to develop AI capabilities with minimal reliance on external actors, enabling nations and organizations to retain greater control over their systems, data, and decision-making processes.[74] As such, open-source solutions can offer characteristics that are particularly valuable to cities, including greater transparency, reduced vendor lock-in, and increased adaptability to local needs and governance requirements.

72 Opensource.com. (n.d.). What is open source? Opensource.com. https://opensource.com/resources/what-open-source.
73 Open Source Initiative. (n.d.). The open source AI definition 1.0. Open Source Initiative. https://opensource.org/ai/faq#what-is-an-ai-system.
74 Gerosa, M., et al. (2025). The State of Sovereign AI: Exploring the Role of Open Source Projects and Global Collaboration in Global AI Strategy. The Linux Foundation. https://www.linuxfoundation.org/hubfs/Research%20Reports/lfr_sovereign_ai_090525a.pdf?hsLang=en#page=6.99.

However, open-source or locally hosted solutions can also present technical challenges. Many open-source solutions require customization, integration with existing government infrastructure, and ongoing technical maintenance. Cities with limited financial resources, technical expertise, or institutional capacity may therefore face barriers to deployment.

Ultimately, cities should carefully assess the benefits and limitations associated with both open-source, locally hosted solutions as well as third-party solutions to select approaches and solutions that best align with their climate goals, institutional values, and governance frameworks. In addition, cities with higher capacity could aim to develop and deploy open-source solutions directly, while cities with less capacity but facing pressing needs could consider third-party providers in the short-term while establishing appropriate safeguards to minimize vendor lock-in and preserve future flexibility. At the same time, these cities can strengthen their capacity to eventually deploy open source solutions.

Getting started with Climate AI – entry points and priorities

Climate AI presents an enormous opportunity for cities to leverage both traditional and emergent technologies to address some of the most pressing climate issues affecting their citizens. While some wealthier cities have the financial resources to invest heavily in AI, such as developing digital twins or bespoke in-house solutions, not all cities in developed countries have the capacity to fully leverage AI solutions. In addition, cities in developing countries or with limited resources are often unable to make comparable investments compared to cities in the Global North. This section provides some guidance for the adoption of Climate AI solutions for cities interested in deploying AI solutions with a particular focus on resource-scarce contexts.

While the Climate AI landscape may seem dominated by cities with more resources, cities with fewer resources or institutional capacity can still explore AI solutions and build a foundation for the future. There are several practical entry points for these cities:

1. **Invest in data literacy and staff capacity**: Building technical expertise can enable staff to better evaluate, adopt, and manage AI solutions in the future. Cities can consider training programs, online courses, and peer learning through city networks which would not require significant financial investments from the get-go. However, city leadership needs to actively prioritize, institutionalize, and support (e.g., by funding or incentivizing) these efforts to effectively build capacity.

2. **Tap on peers, city networks, and other initiatives**: Networks such as Bloomberg Cities, C40 Cities, and the Global Covenant of Mayors for Climate & Energy (GCoM) regularly convene city staff to share their experiences with emerging technologies and can connect cities with peers, industry experts, or researchers that have already piloted or deployed relevant solutions in similar urban, environmental, or legislative contexts. Beyond municipal networks, a range of organizations can support the adoption of Climate AI, including multilateral institutions (e.g. UNESCO,

UNDP, GEF), as well as development banks (e.g. IDB) through regional, national, and project-specific programs. Learning from a peer city's experience, including mistakes and barriers to adoption, can ease a city's adoption of new technologies.

3. **Leverage university and institutional partnerships**: Universities and other institutions (e.g., philanthropic foundations, businesses, start-ups) can be valuable long-term partners for cities that lack the internal technical capacity to adopt and manage Climate AI solutions independently. These institutions often seek real-world governmental partnerships to support applied research or validation and thus, might be willing to provide expertise or their solutions at low or no direct cost.

4. **Evaluate pilot experiences** with commercially available AI products that do not require high institutional capacity or data. Referencing the framework of page 16 of this report, cities with limited institutional capacity should explore commercially available AI Products over raw AI Methods or standalone AI Models / Packages which require significantly greater technical expertise to deploy. AI Products are generally accessible to non-specialist staff and might come with vendor support and defined implementation pathways, making them appropriate for cities without high technical expertise. By starting with budget-friendly, targeted, and standalone pilot implementation of an AI product, cities can build technical capacity and a foundation for future scaling.

5. **Consider the long-term**: Finally, cities with limited resources should approach AI adoption with a long-term perspective. Cities can start with smaller pilots to build institutional knowledge, data infrastructure, and stakeholder confidence to pursue more integrated applications in the future. Cities need not solve their most ambitious urban climate challenges immediately with AI solutions, but instead, aim to build a foundation for future adoption as resources, data, and capacity increase. This is particularly relevant in the context of data governance and sovereignty where cities can initially rely on third-party providers while developing the technical capacity, institutional expertise, and resources required to eventually adopt open-source or locally deployed AI systems for greater transparency and control.

Conclusion

The rapid emergence of AI presents an opportunity for cities to tackle their climate goals with new tools and means. However, the gap between the promise of Climate AI and effective real-life deployment remains significant. As this report has illustrated, the landscape of Climate AI solutions is still maturing with a substantial share of solutions in a pilot or early phase.

This report presents several key points. First, AI is not a uniform category and cities need to look beyond marketing language to examine what a Climate AI solution actually entails in terms of methods, functions, and base technologies. Second, the suitability of a Climate AI solution depends not only on the technology's features and requirements, but also on contextual factors such as a city's data availability and institutional capacity. Last, cities across most levels of readiness can still identify viable entry points in the adoption of Climate AI solutions, whether through plug-and-use commercial solutions that require limited technical expertise, peer learning through city networks, or smaller pilots to build institutional capacity. The experience of municipalities such as Drancy, France demonstrates that meaningful adoption does not necessarily require large-scale transformation and can start with smaller efforts.

Climate AI can be an ally for urban climate action but only if cities ensure that the tools they adopt do not reproduce the very environmental, social, and governance problems they are meant to help solve. Ultimately, cities should approach adoption with clear objectives, realistic expectations, and a commitment to responsible, evidence-informed decision-making.

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