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AI for Spatial Mapping and Analysis

GeoAI Toolkit for Urban Planners

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About this publication

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UNITAC-Hamburg is an innovation lab based in Hamburg, Germany, established in March 2021 by the United Nations Human Settlements Programme (UN-Habitat) in collaboration with the UN Office of Information and Communications Technology (OICT) and HafenCity University (HCU). The lab is funded by the Government of Germany. UNITAC-Hamburg is part of UN-Habitat's People-Centred Smart Cities Flagship program, which provides strategic and technical support on urban digital transformation to national, regional and local governments.

UNITAC-Hamburg supports national and local governments in advancing their urban digital transformation through a multi-level governance approach. It helps build the skills and capabilities needed to design, procure, and use digital technologies ethically, inclusively, and effectively, ensuring that no one is left behind.

The Accelerator works with local governments and stakeholders to identify and co-create data-driven and digital solutions to real-world urban challenges. All projects respond to needs articulated by local leadership and communities, addressing issues such as adequate housing, access to basic services, climate resilience, crisis response, urban recovery, and improved multi-level governance. Through this work, UNITAC accelerates progress toward the Sustainable Development Goals, particularly SDG 11: Sustainable Cities and Communities.

UNITAC-Hamburg promotes open and participatory data governance, digital platforms and technological innovations related to mapping, spatial analysis, data visualization, and people-centred smart cities.

The Accelerator applies research- and development-driven methodologies grounded in in-depth analysis of urban challenges and trends. Its work centres on three thematic areas:

- Open, transparent, and participatory governance of data and digital platforms
- Mapping, spatial analysis, data analytics and visualization
- People-centred smart cities

Across these themes and to support the implementation of the UN-Habitat Strategic Plan 2026-2029, UNITAC prioritizes generating knowledge and practical use cases for smart city governance and the development of frontier technologies, with a particular focus on countries and cities with large informal settlement populations.

This publication has been developed in partnership with ICLEI – Local Governments for Sustainability. ICLEI is a global network working with more than 2500 local and regional governments committed to sustainable urban development. Active in 125+ countries, ICLEI influences sustainability policy and drives local action for low emission, nature-based, equitable, resilient and circular development.

UNITAC HAMBURG United Nations Innovation Technology Accelerator for Cities

UN-HABITAT

United Nations Office of Information and Communications Technology

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Contents

1. Introduction

Urban planning serves as the blueprint for shaping and organising cities, providing a structured framework to address complex challenges and enable opportunities to promote adequate housing for all and sustainable urbanisation. It is a decision-making process aimed at achieving economic, social, cultural, and environmental objectives through the formulation of spatial visions, strategies, and plans, supported by sound policy principles, tools, institutional arrangements, participatory mechanisms, and regulatory procedures (UN-Habitat, 2018). More specifically, urban planning involves the design, evaluation and projection of an organised, coordinated, and standardised physical structure of a city and its underlying infrastructural systems, processes, functions, and services. This encompasses the built form (such as buildings, streets, neighborhoods, residential and commercial areas, parks, etc.), urban infrastructure (including transportation, water supply, communication systems, distributed networks, etc.), ecosystem services (such as energy, raw material, water, air, food, etc.), human services (public services, social services, cultural facilities, etc.), and administration (the delivery of services and provision of facilities to citizens, implementation of mechanisms for adherence to established regulatory frameworks, policy recommendations, various technical and assessment studies) (Bibri, 2018).

As populations grow, cities evolve, and environmental and climate challenges intensify, the importance of effective urban planning becomes evermore critical. From shaping the physical landscape to fostering social cohesion, environmental and economic vitality, planning services are instrumental in building sustainable, resilient, and livable cities for future generations. **Spatial mapping and analysis** play a central role in capturing, analysing and visualising urban complexity, enabling planners to understand how land use, infrastructure, environment and social dynamics interact across space and time. However, traditional geospatial tools and methods (e.g. manual surveys, mapping exercises and conventional GIS modelling) often struggle to keep pace with the speed, scale and complexity of contemporary urban change (Koldasbayeva et al., 2024). In many cases, these methods are time-consuming, labor-intensive, and require a level of GIS that is often lacking. Given limited resources, urban planners are compelled to adopt innovative, resource-efficient, and data-driven geospatial approaches to planning and governance.

Geospatial Artificial Intelligence (GeoAI) is emerging as a transformative technology that integrates artificial intelligence with geospatial analytics to extract meaningful insights from spatial data and support decision-making in spatially informed domains such as urban planning, environmental monitoring, and infrastructure management. It offers significant advantages for urban planners and managers over conventional methods, including enhanced accuracy, greater efficiency in planning and decision-making processes, advanced predictive and analytical capabilities, improved situational awareness, and expanded opportunities for inclusive stakeholder participation. Compared to traditional geospatial methods, GeoAI enables higher accuracy, significantly faster analysis, and cost efficiencies by automating data processing and scaling spatial analysis across large and complex urban areas. Although still an emerging field, GeoAI is rapidly applied across multiple domains of urban planning and management in cities worldwide. Key areas of application include land-use planning, housing and infrastructure management, urban basic services such as energy, waste, water, and mobility systems, as well as public health and safety, disaster management and climate resilience, and urban governance, policy, and administration.

In addition to strategic urban planning, **GeoAI plays a critical role in urban management**, supporting the day-to-day operation, maintenance, and optimisation of urban infrastructure and services. GeoAI enables city administrations and service providers to monitor systems in real time, improve operational efficiency, anticipate service demands, and optimise the allocation of limited resources across sectors. By enhancing situational awareness and enabling predictive maintenance and performance monitoring, GeoAI supports more responsive, cost-effective, and resilient urban service delivery. This operational dimension is particularly relevant in fast-growing cities and resource-constrained contexts, where improving the efficiency and reliability of existing infrastructure and services is as critical as long-term spatial planning.

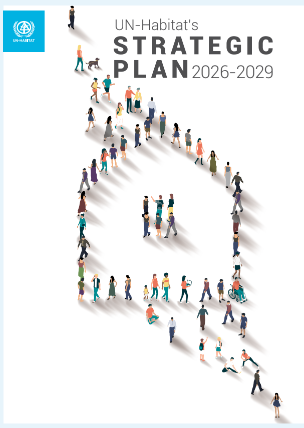
However, various challenges and risks are associated with AI systems, which can hinder the effective integration of GeoAI into urban planning processes. Many city leaders, planners, administrators and managers encounter barriers to integrating AI-powered solutions, including limited technical expertise and skills, insufficient or poor quality of data and gaps in digital infrastructure (UN-Habitat, 2024). Ethical and governance challenges, such as algorithmic bias, data security and privacy, and regulatory compliance, also pose significant obstacles.

Among these challenges, **limitations in knowledge, skills and capacity** consistently emerge as a persistent barrier to the responsible and effective deployment of AI in urban contexts (UN-Habitat, 2024). This can slow down or even prevent cities from harnessing GeoAI opportunities and realising its full potential to enhance access to adequate housing as well as drive more inclusive, resilient, and sustainable urban development. Urban planners and other relevant practitioners should have access to the necessary capacities and resources to acquire the knowledge and skills required for effectively integrating GeoAI solutions.

The toolkit in the remit of UN-Habitat Strategic Plan (2026-2029)

The potential of digital technologies to accelerate sustainable urbanization is recognized in **UN-Habitat's new Strategic Plan (2026-2029),** which confirms the Agency's commitment to a people-centred smart cities approach that fosters international cooperation and promotes academic research and educational initiatives. Smart cities, urban digitalization and innovation are seen as accelerators to address the global challenges mirrored by three impact areas:

- Equitable and inclusive prosperity for poverty eradication
- Preparedness, response, recovery and reconstruction
- Environment and climate action



Specifically, two means of implementation are particularly relevant, namely first, *the "integrated urban and territorial planning, management, investment and finance"* which underscores the importance of evidence-based, spatially informed decision-making to deliver adequate housing, land and basic services. By strengthening knowledge, data, digitalization and institutional capacity, this toolkit directly supports this objective, providing practical guidance on how to integrate GeoAI into urban planning and management workflows to improve the coherence, efficiency and impact of spatial development plans, infrastructure investment and service delivery. Secondly, the *"knowledge, data, digitalization, and capacity development"* section of the plan ties to smart city strategy development. With a focus on improving knowledge and capacities to inform evidence-based, innovative policies on adequate housing, land, and basic services for all, this toolkit further reinforces this goal and **provides practical guidance on how to integrate GeoAI into urban planning practices and workflows.** More specifically, it enhances understanding of how GeoAI can be used and what benefits and potential impact it might bring. In addition, the toolkit offers an integration strategy, including **a step-by-step guidance** to support the effective and responsible adoption of GeoAI in urban planning. The toolkit targets stakeholders involved in spatial and strategic planning such as: urban planners from local and regional governments, city leaders and decision-makers, representatives of relevant line ministries and planning agencies as well as experts and researchers in geospatial technologies, artificial intelligence, and urban analytics.

The toolkit, developed by ICLEI-Local Governments for Sustainability in collaboration with UN-Habitat and UNITAC builds on both entities' portfolio and relevant reports including the UN-Habitat's AI & Cities: Risks, Applications and Governance and the World Smart Cities Outlook 2024. It also responds to the AI capacity needs and gaps identified in the Global Assessment of Responsible AI in Cities. Throughout the toolkit, attention is given to the role of participatory and people-centred processes, highlighting how GeoAI can complement community engagement, citizen-generated data and inclusive decision-making rather than replace them.

The toolkit is structured into six (6) chapters:

- **Chapter 1** sets the foundation for understanding GeoAI, by defining key geospatial terms, technologies, AI techniques and practices
- **Chapter 2** explores recent trends in GeoAI development and adoption in cities

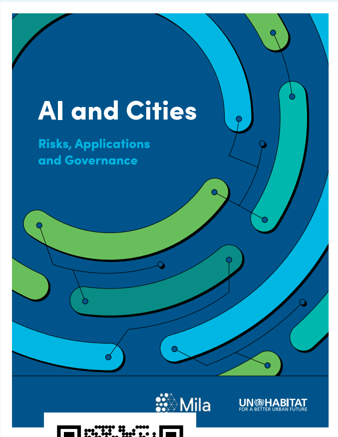
- **Chapter 3** provides insights into GeoAI applications and in key areas of urban planning such as land-use planning, housing and infrastructure management, urban basic services (e.g. energy, waste and water management, mobility), public health and safety, disaster management and climate resilience, governance, policy and administration.

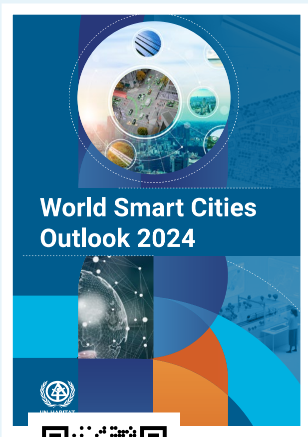
- **Chapter 4** outlines the key opportunities and benefits of GeoAI in urban planning and management

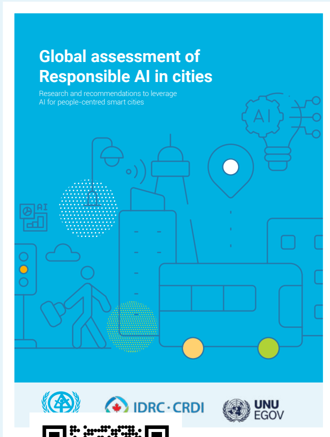
- **Chapter 5** offers a detailed overview of key challenges and risks associated with GeoAI

- **Chapter 6** presents a strategy for integrating GeoAI into traditional urban planning workflows, including a practical step-by-step guidance.

Throughout the toolkit, attention is given to the role of participatory and people-centred processes, highlighting how GeoAI can complement community engagement, citizen-generated data and inclusive decision-making rather than replace them. A comprehensive **compilation of use cases** from across the globe (Annex 1) and of **GeoAI tools, platforms and resources** (Annex 2) enriches the toolkit with practical examples of key application areas of GeoAI in traditional urban planning.







Methodology

The toolkit is informed by extensive desk-based research, drawing on a wide range of sources to ensure a comprehensive and methodologically robust analysis. The study included a systematic review of existing reports and strategic documents produced by UN-Habitat, UNITAC, and other partner organizations, complemented by an examination of recent scientific and academic literature on GeoAI and its applications in urban contexts. Furthermore, technical reports, best practice case studies, and GeoAI manuals were reviewed in order to identify and map available GeoAI, both proprietary and open-source, tools and solutions (Annex 2), and GeoAI use cases (Annex 1). The GeoAI use cases were selected to ensure global diversity, covering a range of regions and application areas. Priority was given to cases showing measurable impact, practical relevance, and proven scalability across multiple cities or regions. To complement the desk research, and in particular the elaboration of selected use cases, a few online consultations with domain experts were conducted. These exchanges provided deeper insights into the practical application of GeoAI solutions across key urban planning domains and enriched the step-by-step guidance with practice-based perspectives.

A validation workshop held during the Smart City Expo World Congress in November 2025 further strengthened the methodological rigor of the toolkit. Through interactive breakout sessions and plenary discussions, practitioners and experts assessed the draft toolkit against real-world urban planning needs, highlighting practical challenges, opportunities, and enabling conditions for effective GeoAI adoption. Their feedback (supplemented by a subsequent review of the revised draft) helped refine the toolkit's structure, guidance, and use cases, ensuring its relevance and applicability across diverse urban contexts.

2. Defining GeoAI and its foundations

This chapter introduces the key GeoAI terms, concepts and technologies to equip planners and other practitioners with the foundational knowledge needed to understand what GeoAI is and how it relates to urban planning practice.

Geospatial Artificial Intelligence (GeoAI) is an emerging interdisciplinary field that brings together artificial intelligence (AI) and geospatial analytics to extract meaningful knowledge from geospatial data. GeoAI has been defined in various ways, reflecting its evolving scope and applications. It draws on a wide range of geospatial technologies and AI techniques to support decision-making processes that are explicitly spatial in nature. Scholars have highlighted different facets of GeoAI: some describe it as a means of analysing large volumes of spatial data at scale (VoPham et al., 2018), while others emphasise its capacity to mimic human spatial reasoning in order to better understand geographic patterns (Lunga et al., 2022). More recent reviews characterise it as a convergence of technologies that render geospatial analysis more scalable, efficient, and accurate across domains such as urban planning, environmental monitoring, and infrastructure management (Boutayeb et al., 2024).

In simple terms, **GeoAI is the integration of geospatial analytics with AI to generate meaningful insights and address urban challenges in a spatial informed manner**. To understand GeoAI better, it helps to break it down into its two main building blocks: **geospatial analytics** and **artificial intelligence**. In the sections below, these core components are defined and explained in detail.

GeoAI analytics

Geospatial analytics has developed from basic cartographic mapping into a key discipline that supports urban planning and spatial decision-making. It integrates multiple forms of analysis to process and visualise location-based data across social, environmental, and infrastructural dimensions. The resulting outputs (i.e. maps, graphs, statistics, and cartograms) enable data-driven decisions that optimise land use, infrastructure, and resource management for more sustainable and resilient cities. Examples include mapping access to housing and building changes to update land-use records, monitoring urban expansion to inform zoning and infrastructure planning, and assessing green-space distribution to promote environmental equity. These capabilities depend on the combination of geospatial data, analytical technologies, and the infrastructure that supports their integration and use. Together, they form the foundation of a rapidly evolving field that continues to expand the ways spatial information is applied to urban planning practice (Arundel et al, 2021).

Box 1 provides a glossary of the main components of geospatial analytics that together form the foundation of this rapidly evolving field.

Box.1

A glossary of geospatial analytics[1]

- **Geospatial data** refers to data about objects, events, or phenomena that have a location on the surface of the Earth. It combines location information (e.g. location of a road, an informal settlement, an earthquake event), attribute information (the characteristics of the object, event, or phenomena concerned), and often also temporal information (the time or life span at which the location and attributes exist).
- **Big data** refers to large, complex geospatial datasets that are difficult to handle with traditional processing techniques. These datasets may include structured, semi-structured, and unstructured information

1 Sources: Esri, n.d.;Dritsas & Trigka, 2025; Hashem et al., 2016;Batty, 2018; Hu & Li, 2017, ITU

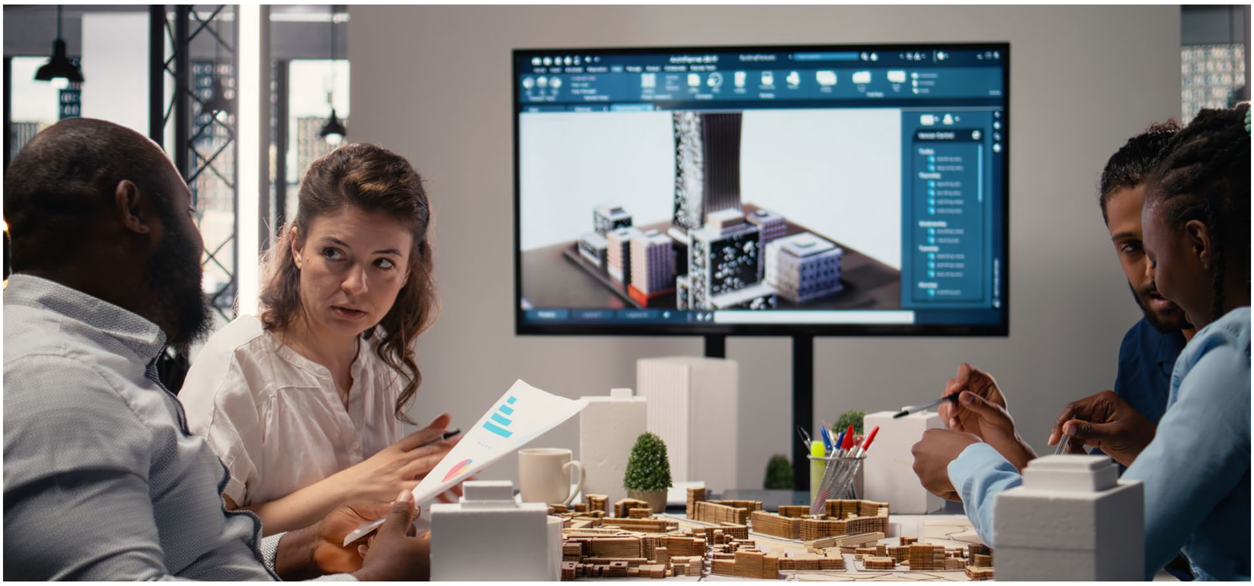
derived from sources such as satellite imagery, remote sensors, and the urban internet of things (IoT) networks.

- **Geographic Information System** (GIS) is a technology that is used to create, manage, analyse, and map all types of data. GIS connects data to a map, integrating location data (where things are) with all types of descriptive information (conditions, context, etc.). This provides a foundation for mapping and analysis that is used in science and almost every industry.
- **Remote sensing technologies**, such as satellite images, drone-based data collection and Light Detection and Ranging (LiDAR), offer high-resolution, up-to-date geospatial data, which is essential for tasks like land cover classification, environmental risk assessment and monitoring of urban sprawl.
- **Internet of Things (IoT)** refers to a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies.
- A **digital twins** is a digital representation of an object of interest and may require different capabilities according to the specific domain of application, such as synchronization between a physical thing and its digital representation, and real-time support.
- **Spatial data infrastructure** refers to the technology, policies, standards, and human resources required to acquire, process, store, and share spatial data in a consistent and reliable way.

Artificial Intelligence (AI)

Recent technological developments have enabled the accelerated development of artificial intelligence (AI). This is a new generation of information technologies that can be defined as the use of techniques, technologies and application systems to replicate, improve and augment human intelligence, such as perception, reasoning, learning, and decision-making (Toosi et al., 2021). AI depends on high-quality data and methods that allow it to analyse information, identify patterns, generate predictions or recommendations, and improve performance over time through continuous learning. Its use is supported by powerful infrastructures such as cloud computing, high-performance computing, and data centers, which provide the storage and processing capacity needed for large-scale analysis (Gartner, 2024).

The integration of AI into geospatial analytics has evolved over several decades. AI became embedded in geographic information systems (GIS) through machine learning and pattern recognition tools, enabling more advanced spatial modeling and data interpretation. Today, AI supports dynamic, data-driven approaches to understanding spatial relationships and change. In this way, it is fundamental to modern geospatial ecosystems (Mai et al, 2025).



To better understand how AI underpins geospatial systems today, key AI-related techniques, practices, and enablers are summarized in **Box 2.**

Box.2

A glossary of AI-related terms, techniques and practices most relevant to GeoAI[2]

AI techniques

- **Machine Learning (ML)** refers to a family of algorithms that learn from data to identify patterns and make decisions or predictions without being explicitly programmed. In **geospatial analytics**, ML can be used, for example, to detect land use changes, classify building types, or predict urban growth based on historical and environmental data.

- **Deep Learning (DL)**, a subfield of ML, differs from traditional ML in the way it processes data and learns patterns. While ML algorithms often rely on manual feature extraction and perform well with structured datasets, DL uses artificial **neural networks** (ANN) with multiple layers to analyse more complex and unstructured data such as aerial imagery or video. ANN is a computing system inspired by the biological neural networks of the human brain. It consists of interconnected processing elements (neurons) that work in unison to recognise patterns and learn from data, mimicking cognitive abilities like adaptation and interpreting fuzzy information. DL has demonstrated particular success in **geospatial analytics** tasks such as automatic detection of informal settlements, identification of green spaces, and segmentation of road networks from satellite images..

- **Natural Language Processing (NLP)** is emerging as an important component of AI, enabling the extraction of location-based insights from unstructured text sources such as planning documents, social media streams, citizen reports and news articles. In geospatial analytics, NLP allows analysts to identify spatially relevant information without manually reviewing vast amounts of text. NLP-based techniques such as geocoding and sentiment analysis can be integrated into geospatial data pipelines, enriching spatial datasets with contextual, human-generated information and supporting more comprehensive spatial decision-making.

- **Knowledge representation:** Capabilities such as knowledge graphs or semantic networks aim to facilitate and accelerate access to, and analysis of, data networks and graphs. Through their representations of knowledge, these mechanisms tend to be more intuitive for specific types of problems. For instance, such representations can map out specific relationships among entities for investigative research, process optimisation or manufacturing asset management purposes.In **geospatial analytics**, knowledge graphs provide a structured way to represent and reason over spatial information. They model entities such as places, events, and observations as nodes, and their spatial or semantic relationships as edges.

- **Agent-based computing:** AI agents are autonomous or semiautonomous software entities that use AI techniques to perceive, make decisions, take actions and achieve goals in their digital or physical environment. In **geospatial analytics**, agent-based systems are used to model and simulate spatial phenomena and interactions among entities such as vehicles, populations, or environmental features

2 Sources: Gartner, 2024; VoPham et al., 2018; Kukreja et al., 2016; Zhu et al.2017; Mai et al, 2025; Esri, n.d; Cai, 2021;Zhu, 2024

AI practices

- **Generative AI:** GenAI can produce new derived versions of content (such as images, video, music, speech, text), strategies, designs and methods by learning from large repositories of original source content. It is a prominent and currently very hyped AI practice, leveraging AI techniques in creative work. Foundation models, such as large language models (LLMs), are a core technique of this practice. In **geospatial analytics**, GenAI is increasingly applied to synthesize spatial data, generate realistic terrain and land-cover simulations, and support spatial reasoning and scenario modeling.

- **Adaptive AI:** Adaptive AI systems aim to continuously learn within runtime and development environments by continually retraining models or adapting them through other mechanisms. Such systems can adapt more quickly to changes in new, real-world circumstances that were not foreseen or available during initial development. In **geospatial analytics**, the application of adaptive AI is still in its early stages. However, its potential is significant, particularly for dynamic environments such as disaster monitoring, climate modeling, or real-time urban mobility analysis.

- **Composite AI:** Composite AI combines different AI techniques to improve the efficiency of learning, broaden the scope of knowledge representations and, ultimately, solve a wider range of business problems in a more efficient manner. Related terms include “hybrid AI,” “neuro-symbolic AI” and “causal AI.” As more organizations realize the limitations of GenAI, they are exploring composite AI to meet their needs. In **geospatial analytics**, its application is still emerging, but early research shows that combining machine learning, knowledge graphs, and symbolic reasoning can enhance spatial understanding and support more adaptive and interpretable analyses.

AI enablers

- **AI-ready data** refers to datasets that are properly curated, structured, and governed to support the training and deployment of AI models. In geospatial analytics, this involves ensuring data quality, consistency, interoperability, and alignment across multiple spatial and temporal sources. AI-ready data must be discoverable, well-documented, and compliant with FAIR (Findable, Accessible, Interoperable, and Reusable) principles to enable scalable, trustworthy, and bias-aware geospatial modelling and decision-making.

- **Cloud computing** provides the scalable computational resources necessary to process and analyse the massive geospatial datasets. By delivering storage, processing, and networking services over the internet, cloud platforms enable AI models to be trained and deployed efficiently across distributed systems, supporting near real-time geospatial analytics and global-scale applications.

- **Edge computing** brings data processing closer to the source of data generation, such as sensors, IoT devices, or cameras deployed in urban environments. By reducing the need to transfer large volumes of data to central servers, it enables faster response times, lower latency, and improved efficiency. Edge computing is particularly valuable in smart city applications, where immediate decisions are needed, such as in traffic management or environmental monitoring.

- **Computing platform** is the infrastructure on which software and AI applications run, consisting of hardware, operating systems, and supporting components such as Application Programming Interfaces (APIs). They provide the computational infrastructure needed to execute AI applications (from local desktop systems to large-scale cloud-based environments).

- **Data centers** host the servers, storage systems, and networking infrastructure that power AI operations. They provide high-performance computing capacity and secure data management needed to handle vast amounts of information. Efficient data centers ensure continuous data flow, model training, and real-time analytics, while maintaining energy efficiency, cybersecurity, and reliable access to the resources that underpin AI and digital twin environments.

3. Recent trends in GeoAI development and adoption

GeoAI has recently emerged as one of the fastest-developing research frontiers in spatial data science. Much of the existing literature as well as an increasing number of research projects and initiatives focus on advancing the development of GeoAI methods and models that can adapt across regions, scales, and urban contexts (Liu & Biljecki, 2022; Mai et al., 2025). Another rapidly evolving research frontier concerns explainable GeoAI, which emphasises visualisation, uncertainty quantification, and interpretability tools that help translate complex AI outputs into actionable insights for urban decision-makers (Roussel, 2024). The ethical dimension of GeoAI is drawing scholarly attention, especially around fairness, privacy, and accountability. As these systems rely on massive amounts of spatial data, there are real risks that algorithms could reinforce existing social and geographic inequalities (De Sabbata et al., 2023; Xia et al., 2025) or expose sensitive information about individuals and communities (Fejerskov, Clausen, & Seddig, 2024; Oluoch, 2025).

Technology companies emerged as a dominant force in GeoAI, with the global market projected to reach between USD 64.6 billion and USD 237.7 billion by 2030, driven by sustained double-digit growth (Precedence Research, 2025). Big technology companies are driving GeoAI innovation by providing powerful tools used across sectors, including urban planning (e.g., Esri's AI-enhanced GIS platforms, Google's Environmental Insights Explorer and Geospatial Reasoning models, and Microsoft's Azure-based GeoAI services such as Azure Maps). At the same time, a fast-growing ecosystem of over 150 GeoAI startups (FlyPix, 2025) is delivering specialised solutions for urban planning, environmental monitoring, and smart city management across global innovation hubs. A common trend across both big tech and startups is the advancement of **digital and virtual twins** (e.g., Google Earth AI, DeepMind's AlphaEarth, and tools from Dassault Systèmes and Ecopia), which are enabling cities to simulate and manage complex challenges such as heatwaves, flooding, and air quality. These developments are reinforced by rapid advances in geospatial data, including increasingly high-resolution satellite imagery that supports more detailed and accurate GeoAI analysis.

There are still no comprehensive statistics on GeoAI adoption in cities, but recent global surveys[3] show that municipalities are already using AI in various urban domains, including urban planning. Although these surveys focus on AI broadly, they likely include GeoAI, as geospatial tools are often embedded within wider smart-city and AI strategies even if not explicitly reported. The key principal fields of AI application in cities include mobility and transport optimisation, waste and water management, energy ,urban planning, public health, and safety; land use, housing and infrastructure (UN-Habitat 2022; Malekzadeh, 2025; Fistola and La Rocca, 2025). The key application areas of GeoAI in urban planning are further outlined in Chapter IV, and Annex 1 presents concrete use cases.

3 E.g. Deloitte 2025, Global Observatory Urban AI (Atlas of Urban AI), Smart City Index 2024

4. GeoAI key application areas related to urban planning

GEOAI can be applied in different areas related to urban planning, as summarized in Table 1 below.

Table 1. Overview of GeoAI application areas and examples of use cases (summary)

GeoAI application areas of urban planning	Examples
Land-use planning, housing and infrastructure management	• Land use classification from imagery • Identification of potential building/housing areas and building footrpints • Detection of informal settlements and illegal housing • Generation of spatial plans and urban renderings • Urban green space and infrastructure management
Mobility and transport optimisation	• Intelligent traffic light control • Traffic flow monitoring and forecasting • Automated road condition monitoring and video surveillance • Electric charging infrastructure and e-mobility networks • Infrastructure support for autonomous vehicles • Mapping informal and paratransit routes
Water management	• Monitoring rainfall, river flow, and groundwater • Mapping and detection of water bodies and utilities • Drought extent mapping with remote sensing • Water quality monitoring with IoT and ML • Water demand forecasting and water loss and unaccounted for water (UFW) reduction • Optimisation of water networks and assets • Water consumption reduction schemes • Customer service enhancement in utilities
Waste management	• Optimised waste collection routes • Real-time monitoring of waste systems, and identification of illegal dumping sites • Automated sorting of recyclables • Forecasting future waste generation
Energy	• Forecasting citywide energy demand and supply • Neighbourhood energy profiling from smart meter data • Building-level energy optimization, and energy sharing schemes • Rooftop solar potential modelling • Optimisation of building HVAC systems • Microgrid and power plant optimisation • Smart street lighting for energy savings
Public safety and health	• Crime prediction, safety hotspot and lightning analysis • Prediction of disease incidence based on spatial factors • Mapping of health resources and accessibility • Modelling/monitoring air pollution and exposure risks, and real time updates for residents
Disaster management, environmental and climate resilience	• Predictive modelling of hazard and vulnerability assessment (flooding, wildfires, heat islands, sea-level rise, stormwater drainage, earthquakes, landslides) • Environmental monitoring of air and water quality, tree canopy and vegetation • Early warning systems and disaster preparedness • Damage detection and situational awareness for response and planning
Administration, policy and governance	• Automated routine administrative tasks such as permit approvals, billing, service requests and citizen engagement • Modernising land cadastres, enhancing property tax collection • Digitising participatory budgeting processes

Real-world case studies showcasing GEOAI use in those domains are included in **Annex 1.**

GeoAI supports land-use planning, housing, and infrastructure by automating tasks that respond to diverse urban growth needs. Key applications include classifying land-use patterns from satellite and aerial imagery (Kumar et al., 2022; Wu et al., 2024), identifying building footprints (see use case 2, Annex 1) and development sites (Rahnemoonfar et al., 2021), detecting illegal housing rentals through real-estate platform data, and predicting neighbourhood change, gentrification, and discrimination in housing markets (Rosen & Garboden, 2024).In many African and Asian cities (where much urban growth occurs in informal settlements) GeoAI adds crucial capabilities such as informal structure detection, slum boundary mapping, service-deficit analysis, and suitability modelling for upgrading. These tools help cities understand the extent, conditions, and growth dynamics of informal areas, which are often poorly documented yet central to housing provision. Improved spatial data also supports identifying sites for new development, planning appropriate densities, and anticipating neighbourhood evolution (see BEAM tool in Box 3 and use case 1 in Annex 1).

Box 3.

BEAM: Using AI to map Informal Settlements in South Africa and Central America

In eThekwini (South Africa), where nearly a quarter of the population lives in informal settlements, outdated data has made it difficult to plan upgrading projects and deliver basic services effectively. To address this challenge, UNITAC developed the Building & Establishment Automated Mapper (BEAM) – an AI-based tool that uses machine learning to rapidly identify and map building structures from aerial imagery. BEAM enables planners to visualise urban footprints,informal structures in the backyards of formal dwellings, generate GIS layers, and track changes in settlement growth and density more efficiently than traditional manual mapping. The BEAM is also deployed in Cape Town and eight cities in Central America, utilising high-resolution satellite imagery. A follow-up project is underway in eThekwini, with an experimental use case aimed at differentiating formal and informal structures from imagery. UNITAC and UN-Habitat's Data and Analytics Unit are now planning to deploy BEAM in Namibia, in partnership with Namibia's National Statistics (Source: UNITAC). For more details, see Annex 1.

GeoAI can also contribute to property and land coding in contexts where ownership records are incomplete, enabling the creation of land cadastres in cities for the first time. These functions are particularly valuable in housing planning, where sound decisions depend on understanding where and how people live. With improved spatial data, planners can identify suitable sites for new development, determine where higher density is appropriate, and anticipate how neighbourhoods are likely to evolve over time. This greater level of insight helps direct limited public resources to priority areas and supports housing strategies that reflect the diverse realities of different communities.

GeoAI can be used to address a wide range of urban mobility and transport-optimisation challenges. Applications include traffic flow prediction, traffic-state recognition, and video-based analysis of movement patterns, which together support adaptive traffic management (Feng et al., 2025). GeoAI also enables monitoring of ride-hailing activity (see use case 11, Annex 1) and infrastructure conditions, such as detecting and classifying road damage for timely maintenance (Feng et al., 2025). Another emerging area is infrastructure for autonomous vehicles, where GeoAI supports mapping, simulation, and safety systems (Dowling et al., 2024; Hopkins, 2023). For example, in São Paulo, Brazil, the Smart Mobility Program applied GeoAI, big-data analytics, and Mobility as a Service (MaaS) to optimise bus operations. Microsimulation models helped test traffic-flow scenarios and informed planning and traffic-control decisions (see use case 3, Annex 1). In developing countries, where informal and paratransit systems account for up to 80% of daily trips (e.g., danfo, keke, boda-boda, matatu), GeoAI offers also particularly valuable capabilities. It can map informal routes, identify high-demand hotspots, analyse safety and congestion patterns, and optimise service frequency and coverage- helping authorities understand and strengthen the mobility systems most residents depend on.

GeoAI has strong potential in water management, supporting rainfall analysis, river-flow monitoring, and groundwater assessment. It can help identify stress zones, detect anomalies, classify pollution sources, and predict contamination spread in rivers and lakes (Bhaskar, 2025; Ponnuru et al., 2025). GeoAI can also map drought extent using satellite imagery and indices such as the NDWI, forecast urban water demand, reduce unaccounted-for water (UFW), optimise allocation, and map water resources and wastewater infrastructure (ADB, 2020). For example, the GeoAI4Water project uses machine-learning and deep-learning models to identify water resources and wastewater treatment plants (WTPs) across Thailand from satellite data and OpenStreetMap. The system mapped 66 WTPs- over 50% more than OSM (39) and more than double the Hydrowaste dataset (26)- revealing infrastructure gaps and improving national coverage (see use case 5, Annex 1).

GeoAI is also transforming the waste management sector, particularly in regions where waste collection and disposal remain a major urban challenge. In waste collection, GeoAI can analyse historical data, traffic patterns, and waste generation rates to optimise collection routes, reducing fuel consumption and emissions. It can support the identification and sorting of recyclables, as well as the detection of illegal dumping sites (see use case 4, Annex 1), thereby increasing the recovery of valuable materials such as plastics, metals, and paper and advancing circular economy initiatives. GeoAI can be also used to forecast future waste generation by incorporating factors such as population density, demographics, historical rates, and external drivers including holidays or major events (Cha et al., 2023b)

GeoAI offers significant potential for improving energy efficiency and optimisation across urban systems. It can predict citywide energy demand and supply, helping planners design resilient infrastructure. Using smart-meter data linked to neighbourhoods, GeoAI can map consumption hotspots, identify energy-poor areas, and guide targeted interventions.Integrating digital twins and deep learning also strengthens rooftop photovoltaic (RPV) modelling by analysing building geometry, orientation, and shading. These insights support policies that encourage rooftop solar adoption, renewable-energy communities, and actions to address energy poverty (Lodhi et al., 2025). GeoAI can further optimise building energy systems by combining spatial building data with weather and usage patterns to reduce waste and improve performance (Mai et al., 2025). Additional applications include smart street lighting, where spatial energy-use data and road networks are analysed to deploy adaptive lighting systems that lower energy consumption and emissions. In Lund, Sweden, for example, the EnergyNet solution uses machine-learning models on geospatial energy data to optimise how locally generated renewable energy is routed and shared, improving both efficiency and resilience[4] .

GeoAI can strengthen public health and safety. Common applications regarding safety include crime forecasting, violation analysis, and safety-hotspot mapping. In Chicago, for example, a GeoAI model using deep graph convolutional networks (GCNs) divided the city into spatial grid cells and analysed crime frequencies and neighbourhood features to classify areas by risk. The system predicted crime hotspots up to a week in advance with roughly 90% accuracy, outperforming traditional methods and offering actionable insights for policing and urban safety planning (Zubair et al., 2025). As regards to public health, GeoAI is particulalry valuable for air-quality management. By integrating traffic flows, land-use maps, weather data, and satellite imagery, GeoAI can identify pollution hotspots, detect spatial trends, and model complex relationships between emissions and urban form, supporting more effective public health planning and regulatory decisions (Feng et al., 2025).

GeoAI can be used to address climate risks, infrastructure vulnerabilities, and environmental quality. GeoAI enhances the ability to map, quantify, and visualise climate risks at the city and neighborhood scales. By fusing satellite imagery, LiDAR, land-use data, and AI/ML techniques, planners can assess exposure to urban flooding, heat islands, energy loss from buildings (see Box 4, use case 10, Annex 1), and sea-level rise (Diehra et al., 2025; Novianti et al., 2025; Takami, 2024). These insights inform zoning, identify priority areas for green infrastructure, and guide capital investments toward resilient building design and city infrastructure, transportation networks, and critical urban services.Stormwater management also benefits from GeoAI, with predictive runoff and inundation modelling based on high-resolution terrain and land-use data. This supports more efficient drainage operations, reduces flood risk, and maintains service continuity (Novianti et al., 2025). Disaster preparedness and response are further enhanced through GeoAI-enabled early-warning systems, damage detection, and post-disaster situational awareness (see use case 9, Annex 1). Mapping tree canopy and vegetation coverage also helps cities reduce heat stress, manage wildfire and flood risks, stabilise slopes, and plan evacuation routes and protective land uses. Environmental monitoring (closely linked to public health) represents another key application. GeoAI can detect air- and water-pollution hotspots, predict contamination trends, and support timely interventions. For air quality, integrating sensor data with meteorological and traffic information enables neighbourhood-level pollution mapping, smog forecasting, and targeted measures such as traffic adjustments or emissions controls.

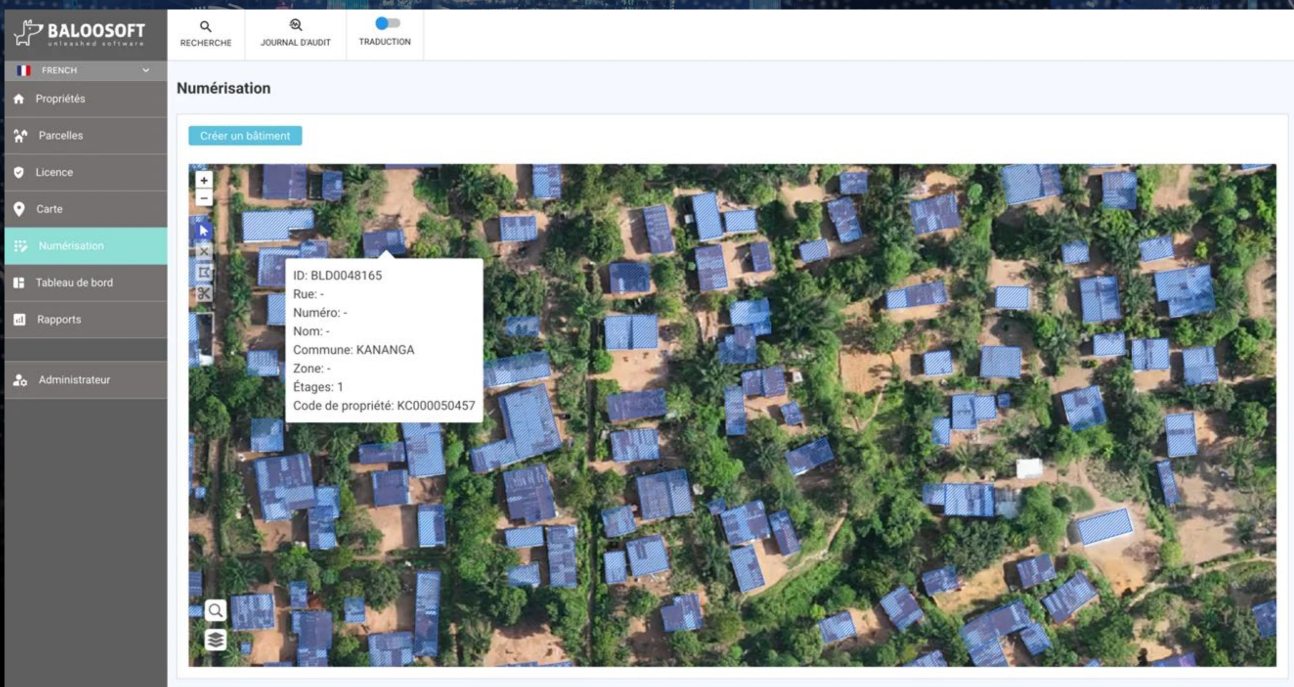
4 Source: Viable Cities

Box. 4

AI and data-driven climate vulnerability map in Barcelona, Spain

Climate Ready Barcelona, one of the ICLEI Action Fund 2.0 projects, develops a Climate Vulnerability Map that combines real geospatial open data and artificial intelligence (AI) to simulate the heating and cooling demand of all residential buildings in the city. It creates a thermal model that predicts the external thermal conditions of each building. It also identifies and maps climate shelters, shaded areas, energy consumption, and income levels, while helping to forecast specific weather conditions. This enables the planning of medium-term building interventions and the protection of residents in areas most affected by climate change in the city. The map is an example of how GeoAI can be used to better detect community needs and optimise institutional and community action. It also supports public services, especially the Energy Advice Points (PAE) of Barcelona. For more details, see Annex 1.

GeoAI can strengthen administration, policy, and governance by speeding up routine tasks such as permit approvals, billing, and service requests. AI chatbots enable 24/7 citizen interaction, while spatial analysis of reported issues helps cities identify problem hotspots and deploy resources more efficiently. GeoAI is also used to modernise land cadastres and improve property tax collection (Prichard 2025; Bergeron et al., 2023). For example, in Kananga, the Local Government Revenue Initiative (LoGRI) and UC Berkeley applied GeoAI to property mapping as part of tax-system reform (see use case 8, Annex 1). Drone imagery was used to automatically detect buildings and generate footprints, which were then refined and verified in the field- providing a faster, more accurate basis for updating the cadastre (Bergeron et al., 2024; Schenker & Somat, 2025).



Screenshot of digitized rooftops over drone imagery of Kananga in Moptax

5. GeoAI opportunities and benefits for urban planning

The integration of GeoAI into the various areas of traditional urban planning brings significant benefits, strengthening the ability of policy-makers and urban planners, administrators and managers to enhance access to adequate housing and design more sustainable, inclusive, and resilient cities, in line with the sustainable development goals, in particular SDG11. Key benefits include:

1. Proactive and evidence-informed decision-making processes. GeoAI generates highly accurate, consistent, and precise information, allowing urban planners to make more informed and evidence-based decisions even in data-scarce contexts (Marasinghe et al., 2024). GeoAI can process and analyse complex datasets with a high degree of reliability, minimizing errors that are often associated with manual or fragmented human analysis. For urban planners, this enhanced precision is cruical in domains where small inaccuracies can have major consequences (e.g. informal settlements, disaster management, waste and water management). The improved accuracy of GeoAI,ensures more reliable datasets, as well as fosters trust and confidence of urban planners, city leaders, stakeholders, and the public in decisions based on these analyses.

2. Enhanced forecasting trends and future scenarios. Utilising historical geospatial data, GeoAI models excel in predictive analytics, and can forecast trends and patterns, such as climate change impacts, population growth, or traffic conditions. These predictions are invaluable for tackling urban challenges, empowering urban planners and managers to enhance planning and city manangement outcomes with insight from spatial patterns and accurate predictions, and optimising the delivery of services (Ben et al., 2024). Predictive analytics also play a crucial role in risk assessment, helping to mitigate potential hazards and natural disasters before they pose a significant threat.

3. GeoAI has strong potential to enhance the delivery and achievement of SDGs, in particular SDG 11. GeoAI, including its strong linkages with the integration of geospatial tools, remote sensing, and big data analytics, is profoundly accelerating progress toward SDG 11 by equipping cities and national statistical offices with deeper, faster, and more actionable intelligence on the dynamics of urbanization.

Today's geospatial ecosystem spans a wide array of tools including Earth Observation imagery from satellites such as Sentinel, Landsat, SDGSAT 1, Planet, high resolution building footprint datasets such as GHSL, Maxar, mobility and transport data, environmental sensors, cadastral and administrative data, and crowdsourced or citizen generated information. When combined with machine learning (ML), natural language processing, predictive analytics, and spatial analytics, it can provide a comprehensive digital representation of urban systems, enabling cities to diagnose challenges and target solutions with unprecedented accuracy.

For SDG 11 and its targets, **GeoAI supports a wide range of analytical and operational functions**. Deep learning techniques are now being used to map informal settlements, classify land use, and track changes in urban expansion to support SDG 11.1 and 11.3. Remote sensing-based vegetation and hydrology indices help quantify access to public green and blue spaces for SDG 11.7. AI-driven transport and mobility analytics can improve understanding of accessibility and service coverage for SDG 11.2. Risk modelling tools integrating hazard data, exposure maps, and socio-economic layers enable more effective disaster risk reduction under SDG 11.5. Meanwhile, geospatial statistical harmonization tools such as the *Degree of Urbanization* allows countries to systematically classify settlements, strengthen national reporting systems, and enhance comparability for global SDG monitoring.

Beyond indicator production, GeoAI also has potential to transform how cities plan and govern themselves. Digital twins and 3D city models now support scenario modelling for land use, housing adequacy, energy efficiency, and climate resilience. Predictive AI tools are also being used to forecast population growth, housing deficits, heat stress, flood risks, and transport demand, allowing cities to proactively plan for future risks and opportunities. Spatial decision support systems, dashboards, and real time data platforms enable local authorities to operationalise evidence, prioritising investments, targeting underserved communities, and evaluating the impact of policies and interventions. Coupled with participatory and citizen data platforms, GeoAI ensures that these insights capture local realities and support inclusive planning and accountability.

Taken together, the expanding suite of geospatial and AI technologies strengthens the full SDG 11 ecosystem, from data generation and indicator measurement to strategic planning, crisis response, and long-term sustainable urban development. By transforming raw spatial information into actionable intelligence, GeoAI will continue to reinforce the link between evidence, policy, and measurable progress, enabling cities to become more inclusive, resilient, safe, and sustainable for all.

4. Increased operational efficiency and productivity. It streamlines the processing of large volumes of geospatial data, automating tasks that traditionally require extensive manual effort. This automation extends from data collection and cleaning to integration and analysis. GeoAI accelerates tasks that would otherwise require time and are labor-intensive, enabling urban planners to process vast amounts of spatial data quickly and thereby achieve higher productivity and efficiency. Cities can further benefit from integrating GeoAI into routine, time-consuming operations, allowing administrations to free up resources for more strategic tasks while also reducing the possibility of human error (Berryhill et al., 2019). These improvements translate into significant cost savings, as optimisation reduces unnecessary tasks, maintenance, and manual data collection (Lodhi et al., 2025; Mai et al., 2025).

5. Accelerated time to situational awareness and response. GeoAI tools enable urban planners to monitor and analyse events, disasters, assets, and entities from sensor and real-time sources such as video to enable quicker response times and proactive decisions. These integrate live data on e.g. traffic flows, air quality, or infrastructure performance into urban planning processes, thus urban planners can make faster, more informed decisions. This allows for quicker interventions such as adapting mobility systems or optimising public space use, and supports more creative, adaptive, and context-sensitive urban planning processes (Pisu & Carta, 2023).

6. Fair participation and representation of diverse stakeholders and communities in urban planning processes. By combining high-resolution geospatial datasets with community-led innovations (e.g. YouthMappers, Map Kibera) and/or citizen-generated inputs (such as data collected through mobile platforms or apps), it provides planners with richer, more inclusive insights that reflect the needs of different groups (Othengrafen et al., 2025). Strong collaboration between local authorities, community representatives, and residents enhances this process, ensuring that data-driven decisions align with local priorities and realities. For example, in Nairobi, Kenya, scientists worked with residents of informal settlements to collect geolocated votes on how deprived or underserved their neighborhoods felt. This citizen-generated data was combined with satellite imagery and analysed using AI models to predict perceived deprivation across the city. The resulting maps revealed hotspots of social and environmental inequality that were not captured in official statistics, helping urban planners identify neighborhoods where targeted interventions were most urgently needed (Abascal et al., 2024).

6. GeoAI challenges and risks for urban planning

Cities face intertwined technical, institutional, governance, and environmental challenges when integrating AI-powered solutions, as highlighted in the UN-Habitat AI & Cities: Risks, Applications and Governance report (UN-Habitat, 2022). Many of these challenges (such as data limitations, weak governance systems, ethical risks, and uneven digital capacity) apply equally to the deployment and use of GeoAI in urban planning, given that GeoAI inherits many of the same dependencies, vulnerabilities, and requirements as broader AI technologies. Specifically, in the GeoAI domain, key challenges and risks include:

1. **Data availability and quality issues.** Many municipalities lack reliable, high-resolution geospatial data due to institutional fragmentation, restrictive data policies, high costs, and uneven access to satellite or LiDAR sources (Kitchin, 2021; Pierdicca & Paolanti, 2022). Existing datasets are often incomplete, inconsistent across departments, or updated irregularly, and **data drift** caused by rapidly changing urban conditions quickly reduces model accuracy (Pelosi, 2025). Common quality issues (such as misclassification of built-up areas and vegetation) further weaken reliability of GeoAI models in e.g. land-use monitoring, risk assessment, or disaster response.

2. **Interoperability is an additional core barrier**, especially as cities attempt to integrate data from IoT devices, digital twins, GIS systems, cadastral records, and AI-driven analytics. Fragmented definitions, incompatible data models, and siloed digital infrastructures often prevent smooth data exchange across municipal departments or between solutions supplied by different vendors. This lack of interoperability undermines the scalability, reliability, and long-term sustainability of GeoAI systems, particularly in cities where legacy systems and new technologies must co-exist.

3. **Digital infrastructure limitations (such as insufficient computing power, unreliable electricity, limited broadband connectivity, and inadequate data-storage or cloud services) further hinder GeoAI deployment.** Because GeoAI depends on robust and continuous digital infrastructure to process large datasets, run models, and maintain real-time systems, cities with weak digital foundations face significant constraints in adopting these technologies. These challenges are particularly acute in many regions and cities of the Global South, where digital infrastructure gaps, high service costs, and limited institutional capacity reinforce an emerging "AI divide" and restrict the scalability and reliability of GeoAI applications (Okolo, 2023; Das, 2025).

4. **Financial and human resources** represent another major barrier. GeoAI requires sustained investment in data acquisition, infrastructure, model development, cloud and computing resources, and skilled personnel. Yet many municipalities operate with tight budgets and procurement systems that are not adapted to rapidly evolving digital technologies (OECD, 2025). Limited financial capacity restricts access to advanced tools, many of which are proprietary, expensive, or require high-performance computing. These constraints are compounded by **limited in-house expertise** in GIS, remote sensing, machine learning, and data governance, leading to dependence on external vendors, risks of vendor lock-in, and solutions poorly aligned with local needs (UN-Habitat, 2022). Low digital literacy among planners and administrators further weakens cities' ability to oversee GeoAI systems effectively.

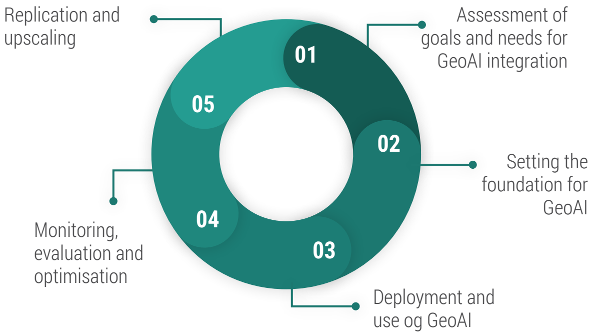
5. **Governance and ethical challenges** add further complexity, particularly in countries where governance systems, data protection laws, and institutional capacities are weak. Regulatory responsibilities for AI, data privacy, and geospatial information are often fragmented across national, regional, and municipal levels, resulting in gaps, overlaps, and inconsistent enforcement (Taeihagh, 2021). These weaknesses amplify risks linked to opaque "black box" GeoAI models, where planners and communities lack the ability to understand, validate, or contest outputs (Hsu & Li, 2023). If underlying datasets reflect historical inequalities, or if models are trained on data from wealthier urban contexts, GeoAI can inadvertently reinforce existing segregation, discrimination, or the exclusion of marginalised communities (UN-Habitat, 2022; Schenker, 2024). This might also include gender-related biases, as many GeoAI models lack gender-disaggregated or intersectional data, limiting their ability to identify and address gendered patterns of vulnerability or exclusion. Weak data protection laws, inadequate cybersecurity, and limited institutional oversight also increase the likelihood that granular geospatial datasets revealing individuals' movements, behaviors, or socio-economic conditions could be misused, leaked, or exploited for political purposes (Rao et al., 2023).

6. Environmental footprint. AI's environmental footprint is emerging as a significant concern, with global AI systems projected to consume 85–134 TWh of electricity and 4.2–6.6 billion m³ of water annually by 2027 (IEA, 2025; Li et al., 2023; Shi et al., 2025). These growing energy and water demands also have implications for the integration of GeoAI into urban planning, particularly in cities already facing resource constraints or climate vulnerabilities. High computational requirements may conflict with local sustainability goals, and the absence of standardised methodologies for measuring the environmental impacts of AI systems makes it difficult for cities to evaluate trade-offs or incorporate GeoAI into long-term climate and resource-management strategies.

7. GeoAI Integration strategy and the step-by-step guide

This chapter introduces a strategy for integrating GeoAI tools into urban planning in order to maximise benefits, while mitigating associated challenges and risks. The strategy provides cities with a practical, step-by-step guide to integrate GeoAI into traditional workflows in a responsible, scalable, and people-centred way. It is organised into five key pillars and twelve (12) steps that guide urban planners from identifying urban challenges and GeoAI needs to deploying and scaling operational GeoAI tools (Fig.1).

Figure 1. GeoAI integration strategy



Given the diversity of municipal contexts, institutional capacities, and data environments, the integration strategy is intended as **adaptable, rather than a prescriptive or one-size-fits-all model**, where the order or number of steps may be adjusted to suit local needs. The strategy is grounded in up-to-date scientific literature on the integration and adoption of ICTs and AI in public administrations and municipalities (e.g., De Silva & Alahakoon, 2022; Brethenoux & Karamouzis, 2020; Yiğitcanlar, 2024; Vatamanu & Tofan, 2025; Eicholz, 2025; Babsek et al., 2025; Marasinghe et al, 2024), and insights from the validation workshop in Barcelona. It also draws on global frameworks that specifically address smart cities, AI, and (digital) transformation in municipal governance - such as ICLEI's Green Climate Cities (GCC) methodology (ICLEI, 2022), UN-Habitat's People-Centred Smart Cities flagship programme, and UNESCO's recommendations on ethical AI. The strategyis aligned to UN-Habitat's People-Centred Smart Cities Flagship Programme which places residents at the heart of design and delivery of technologies and innovation. A people-centred smart city prioritizes inclusivity, transparency, human rights, and sustainability so that digital transformation benefits all communities, especially those historically underserved. Across the steps outlined in this strategy, people's needs, lived experiences, and the potential social risks of GeoAI systems should be considered throughout the lifecycle of GeoAI adoption, including through participatory processes, impact assessments, and other inclusive engagement methods.

Figure 2. GeoAI integration strategy and step-by-step guidance

Pillar 1- Assessment of goals and needs for GeoAI integration	**Step 1** Identification of urban problem and GeoAI use cases **Step 2** Evaluate and validate GeoAI suitability and added value
Pillar 2- Setting the foundation for GeoAI	**Step 3** Analyse and assess technical, institutional and legal context **Step 4** Prepare the geospatial data foundation needed to train and test GeoAI models **Step 5** Select the appropriate GeoAI acquisition pathway
Pillar 3- Deployment and use of GeoAI in urban planning	**Step 6** Develop and validate a prototype to test the core functions of the selected GeoAI tool **Step 7** Align GeoAI outputs into established planning routines **Step 8** Conduct a technical risk analysis
Pillar 4- Monitoring, Evaluation, and Optimisation	**Step 9** Continuously monitor and evaluate performance of the GeoAI tools **Step 10** Optimise and communicate results
Pillar 5- Replication and Upscaling	**Step 11** Conduct a scalability assessment **Step 12** Develop and implement replication and upscaling strategy

Pillar 1- Assessment of goals and needs for GeoAI integration

Step 1 Identification of urban problem and GeoAI use cases

- Start by identifying a specific urban challenge, such as unplanned urban growth, waste management, or urban infrastructure, where GeoAI's strengths, such as predictive analytics or pattern recognition, can outperform traditional manual methods or basic automation. Identifying the problem or urban challenge first also supports a more people-centred approach in GeoAI deployment, by focusing on real needs. The objective is not automation, but better provision of housing, basic services, and integrated informed planning (Brethenoux & Karamouzis,2020; Eicholz, 2025).

- To maximise efficiency and impact of GeoAI, decompose the urban problem into smaller, well-defined aggregated GeoAI use cases, which should be measurable, feasible, and capable of delivering meaningful value (Brethenoux & Karamouzis,2020). This ensures that GeoAI applications remain grounded in practical needs, supported by accessible and reliable data, and aligned with the operational realities of urban planning workflows. For example, in the context of unplanned urban growth, municipalities often face complex and intertwined issues such as informal settlements, insufficient land-use and infrastructure management. By breaking the urban challenge into aggregated use cases, cities can reduce implementation costs by reusing data, mitigate financial and operational risks, and enable scalable GeoAI solutions that can be transferred across different contexts. Where feasible, this step should involve early engagement with affected communities, service users, or civil society actors to validate priorities, surface lived experiences, and avoid technology-driven problem framing.

Step 2 Evaluate and validate GeoAI suitability and added value

- Evaluate whether GeoAI is the most appropriate solution to the identified use cases. Not every use case benefits from GeoAI -some may be addressed more effectively using traditional GIS or simpler models. Assess whether the identified use case (e.g. detection of informal settlements) aligns with existing GeoAI capabilities and municipal priorities (Marasinghe et al, 2024; Boutayeb et al 2024). For example, bring together planners, technical staff, and community representatives (e.g. through a workshop) to map current workflows and approaches (for example, land-use classification, cadastral updates, field-based settlement surveys, or GIS-based transport analyses). Use this exercise to validate the GeoAI use cases and identify where current methods and tools face constraints such as outdated or fragmented spatial data, manual data processing, limited analytical capacity, or high time and financial costs.

- Conduct a cost–benefit analysis to compare GeoAI's expected advantages (e.g. higher accuracy, automation, or predictive insights) with the financial, technical, and institutional resources required for implementation (see step 3). Ensure this evaluation aligns with the municipality's broader AI or digital strategy and considers social, economic, and environmental implications. Based on the results, define a small set of metrics to track GeoAI's added value, such as faster map updates, reduced workload, improved data quality, or increased transparency in planning decisions. A further set of indicators focusing on the risk assesssment factors of privacy, cybersecurity, trust, robustness, explainability, interpretability, usability, and related social implications should also be formulated and evaluated (De Silva & Alahakoon, 2022; Roussel, 2024; Eicholz 2025).

Check-in questions

- What specific urban challenge are we addressing, and where can GeoAI provide added value compared to existing tools or methods?
- Which use cases offer the most practical entry point for GeoAI, and how can we aggregate them and measure whether GeoAI performs better than existing tools or workflows?
- How can we validate that the identified use cases align with GeoAI's capabilities, planning objectives, and peoples' needs, and who should be involved in this process?
- What measurable benefits does GeoAI provide compared to current tools, and do they justify the financial, technical, and institutional effort and costs required?
- Which key performance indicators best capture the expected improvements in efficiency, quality, and governance resulting from GeoAI integration?
- How can we ensure that the GeoAI system's outputs remain understandable, transparent, and trusted by both decision-makers and the public?

Pillar 2- Setting the foundation for GeoAI

Step 3 Analyse and assess technical, institutional and legal context

- Assess the municipality's existing geospatial technologies and infrastructure, including GIS platforms, remote sensing systems, IoT networks, cloud computing environments, and spatial data infrastructures. A clear understanding of these components, i.e. how data are collected, managed, and shared, will help identify strengths and gaps in interoperability, connectivity, and processing capacity (UN-Habitat, 2022). Because GeoAI depends on a robust digital infrastructure (Mai, 2025), this assessment is vital to determine whether the existing digital ecosystem can support large-scale spatial analytics or requires targeted upgrades and partnerships to ensure efficient deployment and use (Babsek et al., 2025)

- Assess the municipality's institutional capacity, including financial and human resources available for acquiring and maintaining GeoAI tools, as well as the human capital required to operate them (Gao, 2023; Fistola et al 2025). Consider whether staff possess technical skills in areas such as GIS, data management and operability, and AI fundamentals (e.g., Python, machine learning, or spatial analytics) and whether continuous training or partnerships are needed. It is equally important to assess the level of public and organisational trust and readiness for innovation- whether leadership, staff and citizens share an understanding of GeoAI's value and feel confident adopting new tools. Building such trust and a collaborative culture is key to ensuring that GeoAI initiatives are embraced and effectively integrated into existing planning routines. Generally GeoAI as any other technology is associated with high implementation costs), assess the availability of financial resources and mobilise adequate funding to acquire and manage urban GeoAI assets such as models, data, skills and infrastructure.

- Analyse how GeoAI can be embedded within existing governance structures and regulatory frameworks at different administrative levels (local, national, regional, international). Review data-sharing mechanisms between departments and check alignment with broader strategic goals such as inclusivity, resilience, and sustainability (Marasinghe et al, 2024; Eicholz, 2025). It is equally important to examine the legal and regulatory environment for GeoAI operations, including data protection, privacy, cybersecurity, interoperability standards, and existing guidelines and strategies for responsible, people-centered and sustainable AI deployment and use. Verify compliance with the relevant local and national requirements and ensure accountability and transparency mechanisms are in place. A clear understanding of the legal and regulatory environment helps ensure that AI initiatives are both compliant and trusted, supporting responsible, transparent, and sustainable practices (De Silva & Alahakoon, 2022;Yiğitcanlar, 2024).

Step 4 Prepare the geospatial data foundation needed to train and test GeoAI models

- Identify and assess the availability of existing satellite, earth observation and spectrum datasets that would be needed for training GeoAI models (Brethenoux & Karamouzis, 2020; Liu 2022; Wang et al 2024). Use GIS platforms and data management tools to compile key layers such as land use, building footprints, environmental and mobility data, and citizen-generated inputs. Complement these with open-source and publicly available datasets (e.g OpenStreetMap, Copernicus Sentinel-2, or Landsat imagery) to fill data gaps, enhance spatial coverage, and reduce costs. Review data coverage and distribution to detect gaps or biases, ensuring that all neighbourhoods and population groups are fairly represented. Apply fairness-aware approaches (e.g. integrating participatory or community-generated datasets and validating results with relevant stakeholders) to improve representativeness and inclusivity in model training.

- Asssess data quality, considering its resolution, frequency, and acquisition method, as these factors strongly influence model accuracy and scalability. High-resolution imagery (10–25 cm) supports detailed feature detection, while coarser data (30–40 cm) may only capture larger structures- highlighting the importance of matching data precision to the specific planning use case. Cities with their own aerial or drone surveys can obtain centimetre-level imagery more efficiently, whereas others may depend on commercial satellite data. In addition, spectral resolution and temporal frequency determine what phenomena can be analysed (e.g., vegetation stress, water turbidity, post-disaster recovery), making multi-source data integration essential to achieve both spatial detail and temporal consistency. However, geospatial datasets can be costly. A practical approach is to use lower-resolution (and therefore less expensive) imagery for citywide coverage, and reserve higher-resolution data for smaller, targeted areas (such as specific districts or neighbourhoods) where greater detail is needed. This helps reduce overall costs while still providing the necessary precision and quality for priority locations.

- Verify that all GeoAI datasets comply with regional, national, and local standards for data protection, privacy, security, and interoperability. Sensitive information should be aggregated or anonymised, and clear data-sharing protocols established to ensure transparency and accountability (Yiğitcanlar, 2024;Eicholz, 2025). At the same time, develop and maintain the datasets needed for GeoAI by defining update cycles, retraining thresholds, and quality-control procedures. Tools such as Google Earth Engine or municipal dashboards can support ongoing checks and documentation. A technology and data-management plan (as well as a designated data manager or team) should oversee updates to mitigate the risk of data drifts, ensure continued compliance, and manage the long-term stewardship of GeoAI datasets.

Step 5 Select the appropriate GeoAI acquisition pathway

- Determine the most suitable pathway for obtaining a GeoAI tool- whether through procurement, co-development, in-house development, or, for many low-capacity municipalities, the use of open-source or freely available tools. Begin by assessing what is realistic within existing technical and institutional capacities, prioritising solutions that are simple to operate, affordable, and require limited specialised expertise. Evaluate each pathway in terms of scalability, interoperability, maintenance needs, and long-term sustainability, ensuring the tool can integrate with existing GIS platforms and data systems.Prioritise tools that follow open standards, offer APIs for integration, and can be adapted as policies, datasets, or planning needs evolve. Where procurement is involved, apply flexible, iterative processes that allow small-scale testing before full deployment, and compare options based not only on cost and performance but also on maintainability and alignment with municipal priorities (Fiermonte et al 2023; OECD, 2025a; Eicholz 2025).

- For cities unable to procure commercial GeoAI solutions, alternative pathways become essential. Beyond traditional municipal budgets, cities can explore alternative financing mechanisms such as development banks, innovation funds, public–private partnerships, philanthropic grants, or national digital-transformation programmes. These can help cover upfront investments in data acquisition, infrastructure, and skills development.

- At the same time, municipalities can collaborate with universities, research institutes, public agencies, civic-tech organisations, and open-source communities to co-develop lightweight, adaptable, and context-appropriate GeoAI tools. Such partnerships reduce costs, strengthen transparency, and build local ownership. They also help ensure that municipalities retain control over how systems are designed, deployed, and maintained- avoiding vendor lock-in and enabling solutions that better reflect local priorities, constraints, and governance realities.

Check-in questions

- What existing geospatial technologies and digital infrastructures are in place, and how well do they support the interoperability, connectivity, and processing needs of GeoAI applications?
- Which financial, human, and organisational capacities are available to support GeoAI integration, and how ready is the municipality to adopt GeoAI tools?
- How can GeoAI be embedded within existing governance and regulatory frameworks while ensuring compliance with data protection, privacy, and ethical standards?
- What geospatial datasets are currently available, and how complete, accurate, and representative are they for training and testing GeoAI models?
- What approach to GeoAI acquisition-purchasing, co-developing, or in-house development- best fits our institutional, operational and technical capacity?
- How can procurement processes remain flexible and transparent, allowing for small-scale testing, iterative learning, and fair comparison between commercial and non-commercial partners?

Pillar 3- Deployment and use of GeoAI in urban planning and management

Step 6 Develop and validate a prototype to test the core functions of the selected GeoAI tool

- Create a small, focused prototype that tests the core functions of the selected GeoAI tools. For procured solutions, this may involve using a vendor-provided demo, sandbox environment, or limited trial licence. For open-source or co-developed tools, this may require installing, configuring, or lightly customising the tool with support from internal staff or partners. The aim is to demonstrate feasibility and value before committing major resources. The validation and testing of the prototype would typically involve a smaller group of experts and users instead of organization-wide access. The primary considerations of deployment are real-time versus batch use of the AI model, the number of end-users and types of applications, the expected formats of output, the expected turnaround time, and the frequency of use (De Silva & Alahakoon, 2022; Babsek et al., 2025).

- After developing the prototype, carry out a test/validation phase to confirm that the GeoAI tool performs reliably and fairly under real conditions. Test the model across diverse neighbourhoods and data scenarios to identify accuracy limits, spatial biases, or usability issues. Engage planners, technical staff, and stakeholders in testing sessions or workshops to gather feedback on usability and interpretability. Emphasize that prototypes are experimental; errors or limitations at this stage are valuable learning opportunities.

- Refine the tool by adjusting data inputs, retraining the model, or improving visualisation and workflow integration based on feedback from planners and technical staff. Document key assumptions, performance thresholds, and risks, and ensure relevant departments (planning, ICT, legal, data protection) review and approve the tool's readiness before moving to full integration (De Silva & Alahakoon, 2022;Yiğitcanlar, 2024; Eicholz, 2025).

Step 7 Align GeoAI outputs into established planning routines

- Use GeoAI to support decisions but not rely solely on it, keeping a balance between the technology offered and the validation by professionals on the ground.

- Where GeoAI outputs inform decisions with direct social impacts (e.g. housing, service prioritisation, risk zoning, or enforcement), cities should establish mechanisms for transparency, explanation, and feedback, enabling communities and stakeholders to understand how GeoAI insights are used and to raise concerns or contest outcomes where appropriate

- Establish clear operational protocols that specify how GeoAI outputs are used in urban planning, including thresholds for uncertainty and conditions that require human review (for instance, predictions with more than a 20% error margin should trigger manual verification). Integrate the model's outputs into specific planning workflows (e.g. site assessments, zoning analysis, environmental impact evaluation, infrastructure prioritisation, and other monitoring tasks) (Eicholz, 2025; Vatamanu & Tofan, 2025).

- Specify clear responsibilities to maintain accountability throughout the process (e.g. who validates results, who approves decisions, who monitors performance, and who updates the protocols). Complement this with clear data-governance procedures (e.g. data-quality checks) and guidelines how GeoAI outputs are used in urban planning, including thresholds for uncertainty and conditions that require human review (for instance, predictions with more than a 20% error margin should trigger manual verification).

Step 8 Conduct a technical risk analysis

- As GeoAI transitions from development into operational use, it becomes embedded within spatial data infrastructures, planning workflows, and other external systems, which introduces new technical, organisational, and societal vulnerabilities. A detailed technical risk classification and analysis must be carried out, building on the preliminary risk assessment. Consequently, the earlier considerations of AI ethics, governance, and regulatory compliance must be extended into the deployment phase, with attention to geospatial-specific issues such as spatial bias, unequal geographic representation, location privacy, and downstream impacts on planning decisions. The assessment should examine risks affecting all relevant stakeholders, organisational units, regulatory requirements, community expectations, and broader social norms associated with geospatial decision-making. A structured risk register and risk assessment matrix can be used to document each identified risk, evaluate its criticality, and outline corresponding mitigation and response strategies (De Silva & Alahakoon, 2022;Babsek et al., 2025)

Check-in questions

- What specific GeoAI use case or planning task are we translating into a prototype, and is its scope narrow enough to allow for meaningful testing and refinement?
- Which approach to prototype development (e.g. adaptation, co-creation, or in-house design) best fits our technical capacity, available data, and institutional context?
- How will we test and validate the GeoAI prototype to ensure its accuracy, fairness, explainability, and robustness across different planning scenarios and user groups?
- How will GeoAI be embedded within existing planning workflows, and what operational rules or thresholds will guide when human review is required?
- Have we identified and documented all geospatial, technical, ethical, and organisational risks that could emerge when GeoAI outputs directly influence planning decisions, and do we have clear mitigation actions for each

Pillar 1- Assessment of goals and needs for GeoAI integration | Pillar 2- Setting the foundation for GeoAI | Pillar 3- Deployment and use of GeoAI in urban planning | Pillar 4- Monitoring, Evaluation, and Optimisation | Pillar 5- Replication and Upscaling

Pillar 4- Monitoring, Evaluation, and Optimisation

Step 9 Continuously monitor and evaluate performance of the GeoAI tools

- Establish a structured process for ongoing monitoring and evaluation of the GeoAI tool. Define how often and by whom the use of the tool will be monitored and maintained. Set key performance indicators (KPIs) for accuracy and fairness (e.g. prediction accuracy above 85%) and data drifts (i.e. indicators tracking when input data changes over time). Monitoring frequency should match the application: daily for emergency systems (e.g., flood alerts or heat-risk models) and monthly or quarterly for urban planning analysis.
- Monitoring and evaluation should also track end-user activity and experience, such as frequency of use, and generated value (i.e. efficiency and productivity, improved decision quality, etc), to understand how effectively the GeoAI system supports planning workflows and to identify where improvements are needed (De Silva & Alahakoon, 2022; Babsek et al., 2025).

Step 10 Optimise and communicate results

- Use the evaluations and the user feedback to further optimise the GeoAI model. Iterate the development process based on the collected insights to improve the performance and relevance of the model.
- Actively communicate the benefits, limitations, and lessons learned from GeoAI deployment to strengthen institutional and public trust, ensuring transparency around how outputs guide decisions.
- Continue investing in staff training, user support, and model refinement to sustain organisational capacity as data sources, policies, and urban conditions evolve.

Pillar 1- Assessment of goals and needs for GeoAI integration | Pillar 2- Setting the foundation for GeoAI | Pillar 3- Deployment and use of GeoAI in urban planning | Pillar 4- Monitoring, Evaluation, and Optimisation | Pillar 5- Replication and Upscaling

Pillar 5- Replication and Upscaling

Step 11 Conduct a scalability assessment

- Once a GeoAI application has demonstrated reliability and value in its initial deployment, deliberate planning is required to consider how it could be scaled up to bring wider benefits - e.g. by extending access to adequate housing to more people, reaching urban areas left behind; by changing or adding to the functionality to increase reach/impact.
- Conduct an assessment of the scalability of the GeoAI solution to explore its potential scalability, given its attributes, data and technological requirements, and other characteristics.

Step 12 Develop and implement replication and upscaling strategy

- Develop and implement an upscaling strategy that sets out actions to achieve upscaling. To achieve a more meaningful upscaling staretgy, build it on existing city targets, processes and plans. Timely development of an upscaling startegy can support broader adoption across cities, different urban contexts and application areas of urban planning, and allow for mobilising public and private finance, as well as create and maintain partnerships (ICLEI, 2019).

Check-in questions (Pillar 4 & 5)

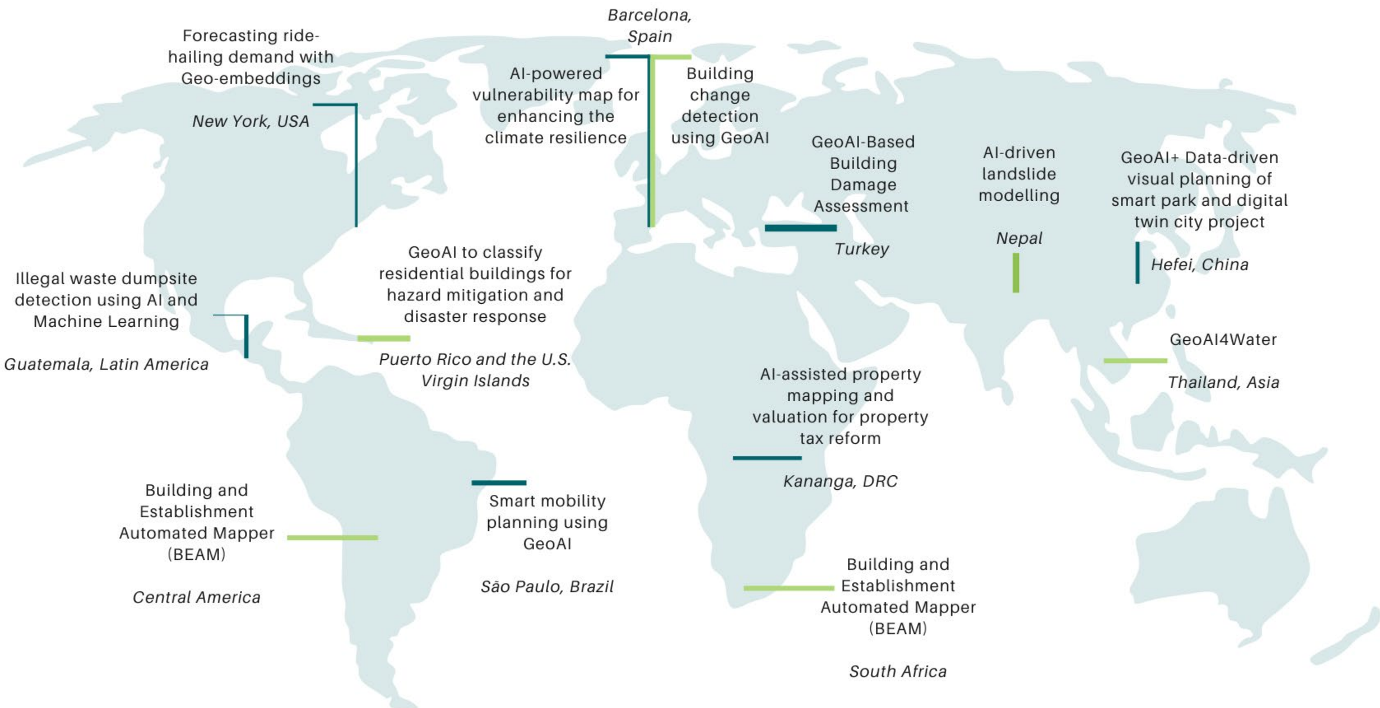
- Which performance indicators and monitoring mechanisms will help ensure that GeoAI outputs remain accurate, reliable, and transparent over time?
- What mechanisms are in place to ensure continuous evaluation and optimisation?
- How will new data, policies, and regulatory changes be incorporated into the GeoAI system to keep it accurate, relevant, and aligned with evolving planning priorities?
- How can results, lessons learned, and capacity-building activities be shared to maintain institutional trust, staff confidence, and public understanding of GeoAI's value?
- Have we assessed whether the GeoAI solution can be reliably transferred to new departments, cities and/or urban planning areas, and do we have an upscaling startegy in place outlining the activities, responsibilities, resources, partnerships, and adaptations required for successful replication?

Annex I. GeoAI Use Cases

Annex I presents twelve (12) GeoAI use cases demonstrating how GeoAI tools are applied in real-world urban planning context. Each case highlights the GeoAI's value in addressing urban challenges, detailing technical approach, data, impacts, scalability, challenges and lessons learned.

The GeoAI use cases were selected to ensure global diversity, covering a range of regions and application areas (Fig.3). Priority was given to cases showing measurable impact, practical relevance, and proven scalability across multiple cities or regions. .

Figure 3. GeoAI use cases across the globe



1. BEAM: AI-based technology designed to detect building footprints through satellite imagery or aerial photography[5]

Key application area: Land use planning, housing and infrastructure management

Title: City/Region: Multiple cities in South Africa and Central America

Informal settlements in the Cape Town area, credit: Filiz Elaerts on Unsplash

Brief description of the tool

The Building and Establishment Automated Mapper (BEAM) is an AI-based tool developed through collaboration between UNITAC-Hamburg, and local partners. The tool uses machine learning to automatically detect building footprints and structures from satellite or aerial imagery. Its use can greatly accelerate the mapping process, reducing the time required from over a year to only 72 hours in eThekwini Municipality. BEAM provides reliable, up-to-date spatial data that strengthens urban planning, service delivery, and evidence-based decision-making for inclusive and sustainable development.

Urban challenge addressed

More than one billion people worldwide live in informal settlements with limited access to adequate housing and essential urban services. Many cities rely on outdated or incomplete spatial data, making it difficult to plan for infrastructure requirements and allocate resources effectively. Manual mapping and ground surveys require extensive time and resources, often leaving large parts of informal areas unrecorded. BEAM responds to this challenge through an automated mapping process that helps municipalities understand settlement growth patterns and improve their capacity to plan and manage urban development more effectively.

Technical approach and data

BEAM applies machine learning to high-resolution aerial or satellite imagery to identify buildings. It uses locally labeled data for training and runs on GPU-enabled infrastructure. Outputs are GIS-compatible and integrated into city databases. Validation combines machine learning metrics and manual checks with municipal partners. The tool relies on aerial, satellite, or drone imagery, supported by partners such as UNOSAT. Data is non-personal, focusing on building shapes and footprints.

5 Sources

- Expert consultation
- UNITAC-Hamburg shares BEAM tool data with the City of Cape Town to address "Incremental Additional Dwellings (IADs)
- BEAM User Manual

Scalability

BEAM has been first deployed in the city of eThekwini (South Africa). It was also replicated in Cape Town, where its use has increased backyard dwelling coverage from 2 percent to 99 percent. The tool has been also upscaled in Central America as part of UN-Habitat Mexico's initiative to develop a regional inventory of informal settlements in Central American capitals. Trained on high-resolution satellite images provided by the United Nations Satellite Centre (UNOSAT), the tool was used in eight cities: Belize City, Guatemala City, San Salvador, Tegucigalpa, Managua, San José, Panama City, Santo Domingo. In this process, BEAM generated shapefiles with building footprints providing a spatial overview of settlement location sizes, extents, and key morphological characteristics.

Impact

BEAM has demonstrated a major improvement in the speed, coverage, and accuracy of spatial data for urban management. It helps city planners to identify growth patterns and better understand the dynamics of informal settlements, enabling municipalities to prioritise upgrading initiatives. Mapping timelines have been reduced from months or years to hours, allowing them to identify and document thousands of previously unrecorded structures. More specifically:

- BEAM mapped **1.530.546** residential and non -residential building footprints across **eThekwini municipal areas**
- **In Cape Town**, an additional **822.390** building footprints were detected using BEAM and integrated into city's geographic database
- BEAM mapped **6324 informal areas** and detected **550.776 buildings** across the eight Central Americal cities
- In eThekwini, BEAM reduced mapping time from months to just **72 hours**, enhancing efficiency and accuracy

Challenges and lessons learned

- **Data availability:** High-resolution imagery is often costly or unavailable, limiting cities' ability to apply the tool.
- **Local labeling needs:** Each new deployment requires locally labeled imagery for model training, which is resource-intensive.
- **Infrastructure:** GPU-enabled hardware or cloud systems are needed to run BEAM efficiently.
- **Technical skills:** Municipalities require GIS and AI expertise to operate and validate outputs.
- **Scope limitation:** The tool detects buildings but cannot yet classify entire settlement types or distinguish informal areas.

Lessons learned: Strong local collaboration is essential to ensure accuracy, contextual relevance, and ownership of results. Access to reliable imagery, adequate computing infrastructure, and trained GIS staff determines whether cities can successfully deploy and maintain the tool. The public release of BEAM-generated datasets, such as in Cape Town, promotes transparency and supports wider learning and replication. Building local technical capacity is key for long-term sustainability. Future development will focus on improving BEAM's ability to distinguish between formal and informal structures, enhancing its usefulness for urban upgrading and progress toward Sustainable Development Goal 11- Sustainable cities and communities.

2. Building Change Detection Using GeoA[6]

Key application area: Land use planning, housing and infrastructure management

Title: City/region: Barcelona, Spain

Changes in buildings, source: Esri ArcGIS Blog

Brief description

The Building Change Detection tool developed by the Institut Cartogràfic i Geològic de Catalunya (ICGC) uses deep learning models integrated in ArcGIS to automatically identify and map new buildings from aerial imagery. It applies pretrained models from the ArcGIS Living Atlas of the World to detect building footprints and assess changes over time, providing an efficient and scalable solution for maintaining up-to-date urban datasets.

Urban challenge

Mapping agencies face increasing difficulty in keeping building inventories and base maps current as urban areas expand rapidly. Manual change detection is time-consuming and costly, limiting the ability of planners to track development dynamics and update spatial data regularly. ICGC sought to automate building change detection across the entire region of Cataluña to support urban planning and land management with timely and reliable data.

Technical approach and data

The workflow used aerial imagery from 2018 and 2022 at 0.25 m resolution provided by ICGC. The data were processed using ArcGIS Pro and pretrained Building Footprint Extraction models from the Living Atlas. Building footprints were extracted for both years and compared to identify new or modified buildings. A multi-resolution deep learning approach was adopted - running the model at several cell sizes (30–50 cm)- to improve detection accuracy for buildings of varying sizes. Post-processing and QA/QC procedures (regularization, filtering, and non-maximum suppression) refined the outputs and removed false positives.

6 **Sources**

- Expert consultation
- ICGC
- Esri ArcGIS Blog

Scalability

The solution uses pretrained models and standard ArcGIS tools, making it easily transferable to other regions or national mapping agencies. The modular design allows adaptation for additional applications such as land cover, infrastructure, or environmental change detection, demonstrating strong scalability potential.

Impact

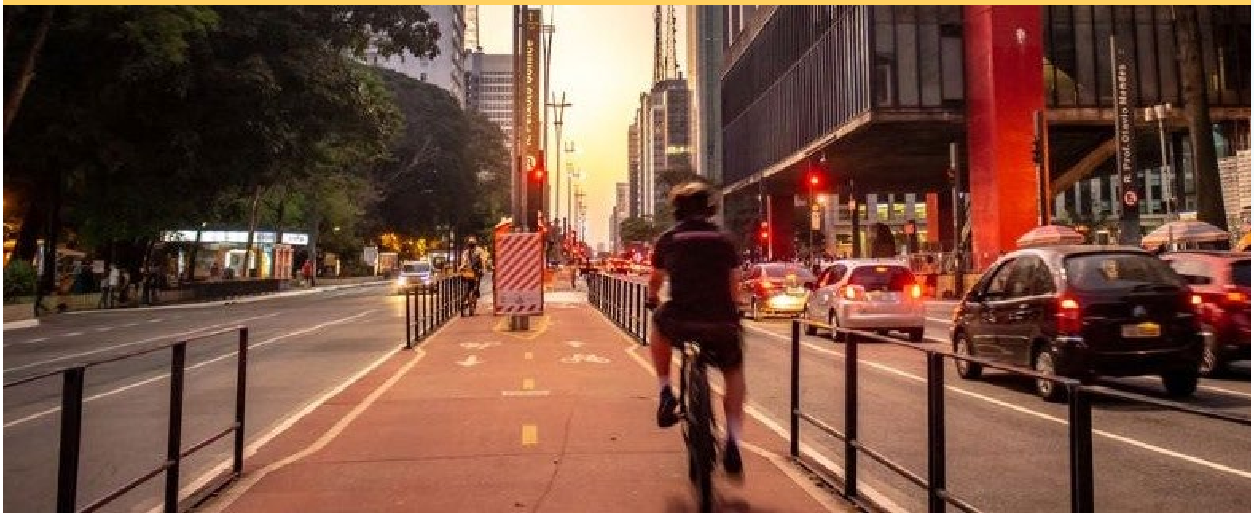
The automated workflow significantly reduced processing time and labor requirements compared to traditional manual mapping. ICGC generated updated building footprint layers and change maps for the entire region, providing planners with actionable insights into urban growth patterns, density, and land use changes. The results were shared through ArcGIS Dashboards, improving transparency and decision-support for regional authorities.

Challenges and lessons learned

- Managing large imagery datasets (over 100 GB) required efficient data storage and processing workflows using mosaic datasets and tile packages.
- Adjusting model resolution and parameters was critical to achieve balanced accuracy across different building types.
- Post-processing proved essential to clean and validate outputs for operational use.
- Building internal technical capacity in GeoAI and automation was key to sustaining the workflow and scaling to other use cases.

3. São Paulo Smart Mobility Program using GeoAI[7]

Key application area: Mobility
City/region: São Paulo, Brazil, South America



São Paulo streets, source: World Bank Group

Brief description

Between 2019 and 2023, the São Paulo City Hall (PMSP) and São Paulo Transport Authority (SPTrans) with support from the World Bank and financed by UK Prosperity Program, implemented a series of activities to modernize the city's public transportation system. The Smart Mobility Program focused on developing a new Operations Center (Centro Operacional – COP), microsimulation of the Aricanduva BRT corridor, and the creation of a governance framework to implement Mobility as a Service (MaaS), a transportation model enabling the integration of different transport modes altogether. The project also supported the design of a georeferenced information system for mobility and accessibility (Sistema de Informações Georreferenciadas de Mobilidade e Acessibilidade - SIGMA), integrating AI/ML and big data analytics.

Urban challenge

In Brazil, where 87% of the total population resides in urban areas, yet there are challenges in urban planning and mobility systems. For many years Brazilian cities were global models of urban transport management. However, in recent decades this process of mobility innovation, which played a fundamental role in developing favorable cost-benefit solutions, has slowed down significantly. While investments in urban transport declined substantially, economic policies implemented at the national level have led to motorization. Over 15 years the motorization rate almost doubled from 23.9 vehicles (2008) to 52.3 vehicles per 100 inhabitants (2021). This led to congestion, inefficient bus operations, and fragmented mobility governance. There is an urgent need to improve planning, monitoring, and coordination of urban mobility using modern digital tools.

7 Sources:

- Lamas et al 2023, São Paulo Smart Mobility Program (English). Washington, D.C. : World Bank Group. http://documents.worldbank.org/curated/en/099042623195019160
- World Bank Blog

Technical approach and methods

The Smart Mobility Program employed a range of advance data analysis tools for urban mobility planning and management. Key interventions included integrating AI, big data analytics, and Mobility as a Service (MaaS) to optimise bus operations and enhance decision-making. Microsimulation models of Aricanduva BRT corridor were developed to test traffic flow scenarios and support decision-making for planning and traffic control. SIGMA (Georeferenced Mobility Information System) was developed to map accessibility, travel demand, and mobility patterns using AI and big data analytics. The COP integrated data streams from multiple agencies (SPTrans, Traffic Engineering Compan, Metro, São Paulo Metropolitan Train Company, police, and emergency services) to support real-time decisions. Advanced studies were also conducted on digitising traffic lights with 5G technology to enable smart traffic management and prioritization of public transportation.

Scalability

The AI-based applications in São Paulo, such as microsimulation models, real-time operations management, smart traffic lights, and integrated data platforms - SIGMA and COP, depicts high scalability potential for other Brazilian and South American cities to optimise bus operations and traffic flow. The models developed can be adapted by other cities facing similar challenges such as congestion and lack of integrated transportation system.

Impact

The application of AI and big data analytics in São Paulo enabled integrated and efficient transport planning by enabling real-time monitoring, predictive analysis, and simulation of the BRT corridors. The digitization of traffic lights supported adaptive traffic signal control, thus reducing traffic congestion and improving travel flow efficiency. Additionally, the program enhanced the regulatory and policy framework governing mobility to deliver more inclusive services, particularly for women and vulnerable groups.

Challenges and lessons learned

The implementation of the Smart Mobility Program in São Paulo encountered several operational and institutional difficulties that affected its continuity and depth of analysis.

- The broad range of potential study topics made prioritisation and scoping difficult.
- Evolving requirements from the São Paulo Municipal Secretariat (PMSP) required frequent adjustments to the project scope.
- Time constraints limited the depth of analysis and prevented pilot testing of proposed actions.
- Leadership changes and complex coordination across multiple institutions disrupted continuity.

➔ The Smart Mobility Program in São Paulo provided valuable insights for future projects of similar scale and complexity. A **key lesson** is the need for contractual flexibility to adapt to evolving requirements of end beneficiaries, ensuring responsiveness throughout implementation. Establishing a project conceptual frameworkis important for coordinating all the activities in order to guarantee consistency and synergies from the project preparation stage to design stage. Adequate time allocation is critical to enable comprehensive analysis and pilot testing. Stable leadership, clearly defined institutional responsibilities, and effective coordination among stakeholders are vital for project efficiency.

4. Illegal waste dumpsite detection using AI and Machine Learning[8]

Key application area: Waste and water management

City/Region: Guatemala , Latin America

Illegal waste dumpsite, source:UNDP, 2025

Brief description

This project, co-led by UNDP Accelerator Lab Guatemala and SDG AI Lab, in collaboration with Politecnico di Milano, aims at identifying illegal waste dumping sites in Guatemala through state-of-the-art GIS, computer vision and machine learning methods. Satellite imagery is used to facilitate efficient and cost-effective monitoring of dumpsites. This joint effort aligns with the strategic goals of the National Development Plan and Country Priorities.

Urban challenge

Guatemala is confronting the challenges posed by the solid waste management at the municipal level and illegal dumping of the harmful waste in areas of biological importance, particularly in critical fluvial and marine-coastal zones like the Motagua River. This river, the largest in Guatemala, is of significant concern as it transports a vast amount of human-made waste to the Atlantic Ocean, leading to a geopolitical crisis with Honduras.

Technical approach and data

The UNDP Guatemala Accelerator Lab and the UNDP Istanbul Centre for Private Sector in Development (ICPSD) SDG AI Lab, in partnership with Politecnico di Milano (Polimi), implemented a project leveraging integration of GeoAI, particularly computer vision and machine learning technique, particularly convolutional neural networks (CNNs). By analyzing satellite imagery and land surface temperature (LST) data, the project successfully identified illegal dumping sites along the Motagua River.

8 Sources

- Video Tutorial
- United Nations Development Programme (UNDP) (2025). Illegal dumpsite detection in Guatemala: Technical Paper. UNDP Istanbul Regional Hub.

Satellite imagery used for the detection of Illegal dump sites in Guatemala included:

- WorldView-3 satellite imagery (50 cm resolution) - Paid
- AGEA orthophotos (resolution 20 cm) - Free
- Google Earth imagery - GeoEye-1 (resolution 50 cm) - Paid; accessed via Google API

GeoAI tools/methods used include:

- Advanced GIS (ArcGIS Pro) - Paid
- ResNet50 architecture - A pre-trained model architecture used in computer vision tasks such as image classification, object detection, and feature extraction. ResNet50 models are freely available in libraries like TensorFlow, PyTorch, and Keras with pre-trained weights.
- Computer Vision Annotation Tool (CVAT) for computer vision - Free/Open Source

Scalability

The project model shows strong potential for scaling both within Guatemala and in other regions facing similar waste challenges. By using cost-efficient imagery sources such as Google API, the approach provides a replicable framework for monitoring illegal landfills in other regions facing similar problems. Long-term scalability can be achieved through human-in-the-loop monitoring approach, API development for stakeholder access, and integration with advanced AI models and benchmark datasets. Expanding and diversifying AI training data will further enhance generalization, enabling nationwide application and global adoption for sustainable waste management.

Impact

The project provided a cost-effective and innovative solution for identifying illegal dumpsites along the Motagua River, significantly reducing the time and resources needed compared to traditional monitoring methods. By combining GeoAI, GIS, and machine learning, it supported evidence-based decision-making and contributed directly to Guatemala National Development Plan by strengthening environmental governance and policy enforcement in Guatemala.

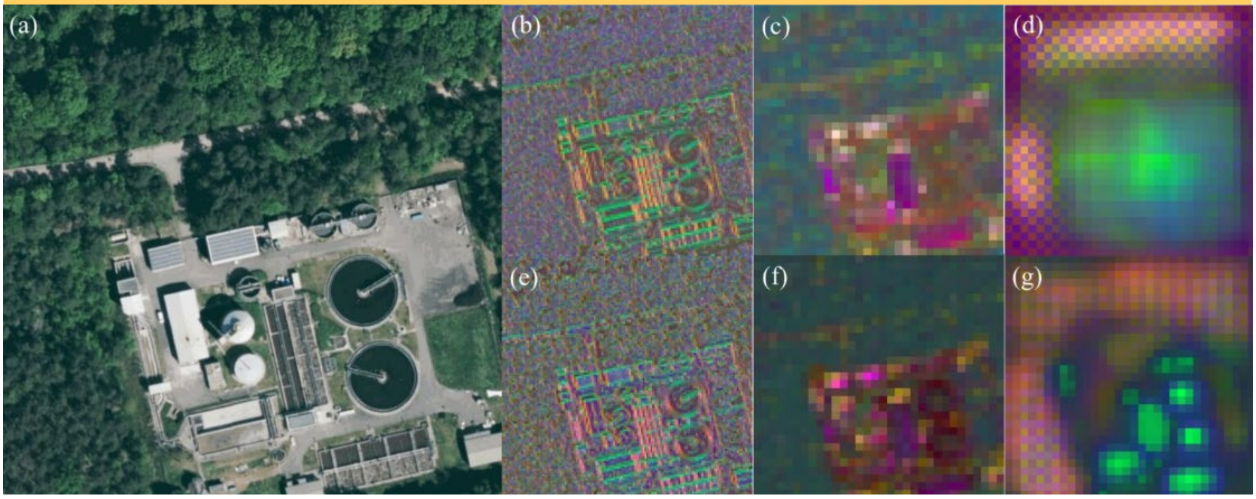
Challenges and lessons learned

Key challenges included limited diversity in datasets, requiring frequent retraining to improve model accuracy, and gaps in local technical capacity to maintain and refine tools. Integration with existing municipal systems proved difficult, while sustainability risks arose from reliance on external funding.

Lessons learned highlight the importance of adapting digital solutions to local contexts, designing tools for retraining and long-term use, integrating with planning systems, and ensuring safeguards, transparency, and inclusive stakeholder engagement for responsible use.

5. GeoAI4Water[9]

Key application area: Waste and water management
City/region: Thailand, Asia



Classifying waste water treatment plants, Source: HeiGIT

Brief description

GeoAI4Water project (phase III launched in 2024) is a collaborative initiative led by HeiGIT (Heidelberg Institute for Geoinformation Technology) that applies AI and satellite imagery to map and classify wastewater treatment plants (WWTPs) across Thailand. Building on earlier project phases (GeoAI4Water I and II), it integrates Sentinel-2 and PlanetScope data with deep learning models and a human-in-the-loop process to enhance accuracy. The project helped to strengthen national datasets and demonstrates the potential of GeoAI for sustainable infrastructure planning in developing regions.

Urban challenge

Access to clean water is fundamental for climate resilience, water resource management, and sustainable development. WWTPs are vital for purifying wastewater and supporting environmental and climate strategies. Yet accurate information about their location and performance is often lacking, especially in developing regions with limited access to safe water and opportunities for reuse of treated wastewater. During natural disasters, the ability to rapidly identify urban utility infrastructure and allocate water resources for purposes such as firefighting is critical, as delays can severely impede relief and response efforts.

Technical approach and data

GeoAI4Water is a innovative solution that utilises machine learning and deep learning models to map water resources and WWTPs across Thailand from satellite imagery and OpenStreetMap (OSM). This tool will empower urban planners, city governments, and responders with the data needed to enhance water resource management, meet environmental standards, and minimize the impacts of disasters . The workflow for detecting WWTPs began with applying smart filtering to Sentinel-2 Near Infrared (NIR) band and PlanetScope imagery were used to identify potential water bodies which are medium-resolution imagery. The next step, extraction using YOLOv6 pre-trained deep learning model applied to very high-resolution BING imagery at zoom level 19 (available only for Bangkok and Rayong only) and zoom level 17 imagery (available for all of Thailand), to locate the WWTPs. Data Sources used for GeoAI4Water applications included:

9 Sources
- GeoAI4Water Blog 1
- GeoAI4Water Blog 2
- GeoAI4Water Blog 3
- Randhawa et al, 2023

- Sentinel-2 (spatial resolution 10m) - Free/Open Source
- PlanetScope (spatial resolution 4m) - Paid
- Zoom 17 (spatial resolution 1.2m) - Paid
- BING - Zoom 19 (spatial resolution 30cm) - Paid
- Open Street Map Data - Free/Open Source
- Hydrowaste - Free/Open Source
- ClimateTrace - Free/Open Source

Scalability

The GeoAI4Water model demonstrates scalability for national and regional applications. This approach can be scaled to other countries in the Global South, where gaps in infrastructure data and coverage of high-resolution imagery are common. The cloud-based processing will allow the tool to be applied across millions of square kilometers efficiently, while the integration of human-in-the-loop verification will ensure reliability. The methodology is also adaptable to infrastructure and use-cases beyond WWTPs, enabling the mapping of aquaculture sites, industrial ponds, and emission hotspots. With refinements, it could support urban planning, disaster and climate preparedness, and regional GHG monitoring strategies.

Impact

The GeoAI4Water model applied a human-in-the-loop verification process to identify 66 WWTPs sites. Comparison with open-source datasets such as Hydrowaste and OSM revealed significant gaps in existing datasets, whereas GeoAI4Water captured more new WWTP sites, highlighting the outdated and incomplete nature of existing datasets. The human-in-the-loop process not only improved accuracy but also uncovered hidden insights, such as aquaculture and shrimp farms resembling WWTPs.

Challenges and lessons learned

The implementation of the wastewater treatment plant (WWTP) detection model in Thailand faced several technical and data-related challenges that affected accuracy and scalability.

- **Limited data availability**: Access to high-resolution (30 cm) satellite imagery from BING was restricted, reducing the model's full-scale applicability across the country.
- **Lower spatial resolution:** The model relied on Zoom 17 satellite imagery (1.2 m), which decreased the precision of WWTP identification and overall model performance.
- **Classification issues**: Certain land uses, such as shrimp farms and palm oil ponds with aeration systems, closely resembled WWTPs, causing false detections and uncertainty.
- **Dependence on manual verification:** Although the Smart Filtering step reduced false positives, accuracy still depended on human validation and manual reclassification.
- **Outdated reference datasets**: Open-source datasets such as OSM, Hydrowaste, and ClimateTrace were often outdated or incomplete, limiting the reliability of cross-validation and benchmarking.

➔ A key lesson learnt is that AI alone cannot fully replace expert oversight; hybrid approaches combining automation, spectral analysis, and human validation are essential. Another takeaway is the potential of multi-sensor integration (Sentinel-2 + PlanetScope) to maintain accuracy even with limited coverage of high resolution satellite imagery, making this methodology both flexible and scalable to other regions.

6.GeoAI to classify residential buildings for hazard mitigation and disaster response[10]

Key application area: Disaster management and climate resilience

Title: City/Region: Puerto Rico and the US Virgin Islands, Latin America and the Caribbean

Building damage assessment results, source: UNDRR, 2025

Brief description

In regions highly exposed to hurricanes, earthquakes, and other natural hazards, maintaining an accurate and updated building inventory is critical to effectively assess disaster preparedness and provide the right response to climate risks. In Puerto Rico and the US Virgin Islands, the lack of detailed, scalable building data can prevent proper mitigation planning and limit the possibilities for risk assessment.

To address this gap, AtkinsRéalis has developed a GeoAI-based machine learning method using aerial photography to automatically classify and extract key building features. The project has been supported by the Federal Emergency Management Agency (FEMA). Together, they have developed a detailed, geospatially referenced building database to allow for loss estimation and hazard modelling.

Urban challenge

Accurate and detailed building data is essential to allow for risk assessment and emergency planning, to reduce the damaging capacity of climate-related natural hazards. However, in many climate-sensitive regions such as Puerto Rico and the US Virgin Islands, available information is often outdated, inconsistent or incomplete. Besides that, traditional field surveys to update building inventories can be costly and time-intensive, overcoming authorities' data-collection capacity. This, considering also that data collection can takes years to complete, leaves planners working on emergency contexts without timely data. As such, the challenge of this initiative was to create a fast, scalable and reliable solution to map and classify residential building features across a large and diverse territory to improve disaster readiness and the right allocation of resources.

Technical approach and data

The GeoAI solution integrated remotely gathered aerial imagery and building-footprint data within a machine learning (ML) workflow to identify and classify residential structures in Puerto Rico and the US Virgin Islands. This was developed my AtkinsRéalis, supporting FEMA in creating a database for Hazus, which supports in hazard mitigation and disaster response. To carry on the task, two machine

10 Sources

- United Nations Office for Disaster Risk Reduction (UNDRR)(2025). Special report on the use of Technology for Disaster Risk Reduction.

learning methods were used: a boosted regression tree model (BRTM) for structured attribution prediction, and a Convolutional Neutral Network (CNN) for visual pattern recognition. Both models were trained on high-resolution aerial images from Puerto Rico and the US Virgin Islands. The combined approach improved the strengths of each algorithm — with the BRTM capturing numerical and tabular features and the CNN analyzing image-based visual cues.

Scalability

The success of this initiative in Puerto Rico and the US Virgin Islands highlights the scalability potential of GeoAI-based building inventory methods. Being the model data-driven and modular, it can be rapidly adapted in other contexts by using local aerial imagery and building-footprint datasets. This makes the approach highly transferable to other hazard-prone regions and developing countries seeking to modernize disaster risk databases and preparedness systems. The initiative demonstrates that combining multiple ML techniques within a GeoAI framework allows for rapid, large-scale, and affordable risk assessment across diverse geographic contexts.

Impact

The application of GeoAI for building classification had a substantial impact on disaster management and risk assessment in the region, with the ML models achieving 80–90% accuracy, levels comparable to human-led surveys but at a fraction of the time and cost. This has enabled FEMA to prepare more accurate risk assessments, develop building inventory for hazard modelling and disaster planning, and better allocate resources to protect lives and property. The approach also demonstrated that ML can be versatile and robust when different techniques are combined to capture both structured data and visual image features. The automation of building detection and classification has significantly contributed to reduce the time and cost required for large-scale data collection while maintaining analytical rigor.

Challenges and lessons learnt

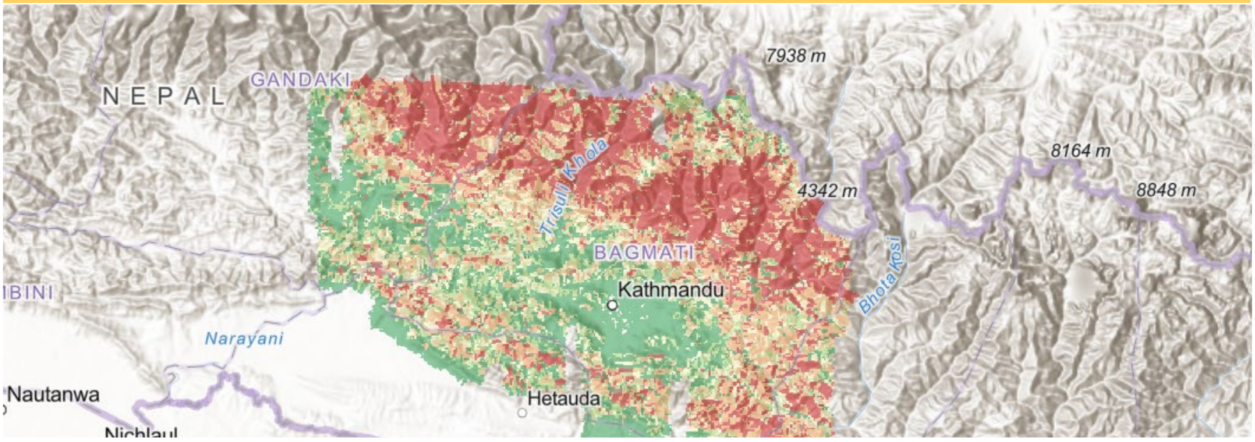
Several lessons emerged from this initiative.

- First, scalability is a major advantage of ML over traditional methods, allowing agencies to conduct rapid assessments without the need for labour-intensive surveys.
- Second, the combination of multiple ML techniques, such as BRTM and CNN, enhances accuracy and robustness, showing that methodological flexibility is critical.
- Lastly, the quality of aerial imagery and building-footprint datasets directly impacts on the reliability of the results, highlighting the importance of investing in high-quality data.

7.AI-driven Landslide Modelling[11]

Key application area: Disaster management and climate resilience

TitleCity/region: Nepal



Landslide susceptibility with explainable AI, source: ArcGIS

Brief description

This project uses a transparent deep learning model to predict landslide risk in Nepal after the 2015 Gorkha earthquake. Landslide susceptibility models often struggle with balancing interpretability and predictive power. Traditional statistical approaches provide transparency but may lack accuracy, while more advanced machine learning models often behave as "black boxes," making it difficult to understand how predictions are generated. This practice addresses the need for models that are both reliable and explainable, particularly in high-risk, data-limited settings. The integration of SHAP into the modeling workflow allows for both global and local interpretations of model behavior, helping decision makers trust and understand the results, which is crucial for planning and disaster risk reduction.

Urban challenge

The region of Nepal and its surroundings, including parts of south-western China and north-eastern India, was tragically hit by the earthquake Gorkha, which killed 8,962 people. Earthquakes can cause landslides by weakening rock and soil, triggering them through shaking or causing long-term destabilization, even years after the initial event. These landslides can be a major hazard, causing immediate destruction and creating secondary risks like flooding from blocked rivers or damaging infrastructure like roads and utility lines. The long-term effects can persist, with renewed landslide activity triggered by aftershocks or rain, and a slow recovery of the landscape taking decades. For that reason, accurately predicting where landslides are more likely to take place becomes of crucial importance to take preventive measures to reduce the landslide risk and/or decrease the damages landslides produce to the population, villages and infrastructure.

11 Sources

- Dahal, A., Lombardo, L. "Explainable Artificial Intelligence in Geoscience: A Glimpse into the Future of Landslide Susceptibility Modeling." Computers & Geosciences, ScienceDirect, 17 Apr. 2023, www.sciencedirect.com/science/article/pii/S0098300423000687?via%3Dihub
- ArcGIS Map: https://arcg.is/0unziD

Technical approach and data

The algorithms are able to predict landslide risk by training a neural network on 13 environmental factors and geological predictors, aggregated at the slope-unit level, to produce susceptibility scores for over 16,000 terrain units. It identifies areas most likely to experience landslides, and what makes this approach special is its use of SHapley Additive exPlanations (SHAP) - a technique that shows how each factor influences the prediction - providing users with insights into the influence of each input factor on individual predictions, making the results more transparent and actionable. An interactive online map helps planners and disaster managers explore the results and use them in local planning. The study utilized a variety of open-source and remote sensing datasets, including a detailed landslide inventory from the Gorkha earthquake, rainfall data from CHIRPS, terrain variables from SRTM-derived digital elevation models, and soil properties from the SoilGrid database. Geological data from the NASA USGS were also included. These datasets were aggregated at the slope-unit level using the r.slopeunits tool, which delineates terrain into hydrologically and geomorphologically consistent mapping units. A fully connected artificial neural network with 12 hidden layers was designed to process 13 normalized features, including both continuous and categorical data. The model was trained using weighted binary cross-entropy to address class imbalance and optimized using the Adam optimizer. SHAP was applied post-training to generate interpretable outputs, revealing the contribution of each predictor to the final susceptibility score of each mapping unit. The results were deployed in an ArcGIS Online interface that allows users to explore model predictions and associated explanations interactively.

Scalability

This project developed algorithms to predict landslides in a given geographical area, as shown in the image above: each colour represents a different level of risk. The algorithms have been tested using data of the Gorkha earthquake, and several predictors which were carefully chosen and modelled to represent the geographical area to be analyzed. In this sense, there is potential to adapt the software developed to be used in other areas, as long as the parameters used by the algorithms are adapted to the specificities of this new regions. In addition, the fact that the algorithms have the component of being explainable can be a differential factor when scientists and city/region officials consider which landslide susceptibility models to use.

Impact

The explainable deep learning model demonstrated high predictive performance, confirming its utility for post earthquake landslide susceptibility assessment. The ability to interpret model outputs using SHAP helped identify slope steepness, ground shaking, and soil texture as key contributors to landslide risk in the study area. These findings are not only scientifically meaningful but also useful for hazard mitigation planning. The interactive Web-GIS platform has increased accessibility to the model's outputs and helped local planners and engineers better understand landslide risks. The tool has already been used in training events in Nepal and is helping improve local hazard maps. Early feedback suggests that the system has begun informing updates to local hazard zoning practices, highlighting its practical applications.

Challenges and lessons learned

One of the key insights from this practice is that neural networks do not need to be overly complex to be effective. By using a relatively simple architecture, the model remained interpretable without sacrificing accuracy. This reinforces the importance of balancing model sophistication with clarity, especially in applied contexts. Spatially aware validation techniques, such as regional cross-validation, were also essential in assessing the model's generalization capacity. Without these, performance estimates could be misleading due to spatial clustering in the data. Another important takeaway is the benefit of using slope units rather than arbitrary grid cells for landslide modeling, as they better reflect the terrain's natural structure. Looking ahead, incorporating physics-informed constraints into deep learning models could improve both accuracy and trustworthiness, especially for applications in dynamic or climate-sensitive regions.

8. AI-assisted property mapping and valuation for property tax reform[12]

Key application area: Administration, policy and governance
City/region: Kananga, Democratic Republic of the Congo (DRC)

Image: Screenshot of digitized rooftops over drone imagery of Kananga in Moptax, source: LOGRI

Brief description

The GeoAI tools developed under the Kananga property tax reform initiatives integrate AI-assisted property mapping and valuation to support the development of a more data-driven, fair, and efficient property tax system. A pilot project applied machine learning and computer vision models to predict property values and build a property valuation roll. At a larger scale, an algorithm was trained to detect built structures and generate building footprints from drone imagery, supporting comprehensive property identification and mapping.

Urban challenge

Kananga, the capital of Kasaï-Central province, is home to an estimated 1 to 2 million people (Balán et al., 2022). In 2015, tax revenue in the province stood at just $0.23 per capita annually (Weigel, 2020), severely limiting the government's ability to deliver basic services. Property tax accounts for roughly 26% of total provincial revenue (Balán et al., 2022) - a relatively low share given its potential. The existing property tax system was highly dysfunctional, mainly due to incomplete property identification and the absence of an up-to-date and comprehensive valuation roll. These issues drastically reduced revenue potential and created an inequitable system where many properties were not identified, valued, and taxed. In the context of property tax reform initiatives in 2019 and 2023, GeoAI tools were tested to help address challenges related to property identification and valuation.

12 Sources:

- Expert consultation
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- Schenker, X. & Somat, A., (2025). Building local government capacity for property tax reform in Kananga, DRC. Local Government Revenue Initiative (LoGRI). Retrieved from https://logri.org/2025/04/building-local-government-capacity-for-property-tax-reform- in-kananga-drc/
- Weigel, J. L. (2020). The participation dividend of taxation: How citizens in Congo engage more with the state when it tries to tax them. The Quarterly Journal of Economics, 135(4), 1849–1903.

Technical approach and data

In 2019, a pilot study led by ICTD, UC Berkeley, and the Provincial Government of Kasaï-Central developed and tested machine learning and computer vision models to predict property values and build a valuation roll in Kananga. The machine learning approach trained several algorithms on the land- surveyor-assessed sample, using property characteristics from an administrative census to predict the value of all properties in the city. The computer vision approach, by contrast, trained deep convolutional neural networks (CNNs) on features extracted from property photographs, allowing valuation predictions based on visual attributes rather than administrative data (Bergeron et al., 2023).In 2023, a comprehensive property tax reform was designed and successfully implemented in Kananga (Local Government Revenue Initiative, 2025). As part of this reform, a new GeoAI tool was developed and deployed to support property identification and mapping. The team commissioned high-resolution drone imagery and trained an algorithm to automatically detect built structures and generate building footprints, which then served as the baseline for manual desk-based corrections and ground truthing. For the valuation component of this broader reform, property values were established through manual data collection, not through the machine learning or computer vision methods tested in 2019. Enumerators conducted field surveys to collect detailed property characteristics, which were later used to calibrate a valuation model tailored to the local context (Schenker & Somat, 2025).

Scalability

For valuation purposes, the LoGRI team concludes that in low-income countries, the benefits of using complex machine learning or computer vision models are limited and often do not justify the effort compared to manual data collection approaches. When deployed at scale these technologies can also face administrative challenges in low-capacity settings, as well as public trust and comprehension issues. The use of AI for building footprint extraction is improving, but error rates remain high, requiring substantial manual desk-based cleaning and ground verification - particularly in dense and informal urban areas that are increasingly common across rapidly urbanising African cities. These challenges are often greater in lower-income contexts, where AI tools trained on data from wealthier cities perform less accurately. However, depending on the urban layout and planning quality, AI-assisted mapping can still offer significant time and cost efficiencies for identifying built structures and generating building footprints at large scale- provided it is combined with thorough manual field verification.

Impact

The machine learning model, which combined several decision-tree algorithms, predicted property values with moderate accuracy, explaining roughly 60% of the variation in actual values. In contrast, the computer vision models, which relied on neural networks trained on property images, were less precise, capturing about 40% of the variation (Bergeron et al., 2023). Overall, machine learning approaches using structured administrative data proved more reliable than image-based models that depended solely on visual features. Yet, while promising, these AI-driven methods remained less accurate than manual data collection for administrative valuation purposes. The use of an algorithm for building identification and footprint extraction enabled the creation of a georeferenced inventory of over 130,000 buildings, covering approximately 9,000 hectares across Kananga. The entire process - from drone image capture to the finalized geodatabase, including algorithmic processing and manual corrections- was completed in about three months, demonstrating the efficiency and scalability of the approach. However, high error rates made ground truthing absolutely essential to correct inconsistencies generated by the algorithm.

Challenges and lessons learned

The Kananga experience illustrates both the promise and the limitations of using AI in property tax administration. While AI tools can enhance efficiency and automate complex tasks, their accuracy remains limited, especially in low-income and data-scarce environments. In practice, these technologies are often most effective when combined with manual verification and field data collection, rather than used as standalone solutions. The machine learning and computer vision approaches for valuation remain largely an experimental tool, with error rates too high for administrative valuation. AI-assisted mapping can significantly speed up property identification, but still requires substantial manual cleaning and ground truthing. More broadly, these experiences reveal the administrative and technical constraints of scaling such tools in low-capacity contexts. Most rely on international expertise and external data processing, which raises concerns about long-term sustainability, knowledge transfer, and local ownership. The key lesson is that AI can play a valuable complementary role but it must be applied strategically and pragmatically, with strong local capacity and manual oversight at its core.

9. GeoAI-Based Building Damage Assessment for the 2023 Turkey Earthquake[13]

Key application area: Disaster management, housing and infrastructure

City/region: Multiple cities in southern Turkey - Kahramanmaraş (Marash), Türkoğlu, Nurdağı, and Islahiye

Extensive damage around the Culture Park area of Marash. Planet Labs PBC, February 9th., source: Microsoft Research

Brief description

A toolkit developed by Microsoft Research ("AI for Good" labs) in partnership with Planet Labs PBC for post-disaster building damage assessment in the aftermath of the 6 February 2023 earthquake in Turkey. The system uses high-resolution satellite imagery (Planet 50 cm, Maxar Technologies 30 cm) and pre-trained convolutional neural network (CNN) models on the xBD dataset to perform semantic segmentation of damage: each pixel is classified as damaged building, undamaged building, or background. Annotation tools (an open-source "satellite imagery labeling tool" published on GitHub) were used to fine-tune the model for the specific cities

Urban challenge

Southern Turkey suffers from frequent large earthquakes and rapid urbanisation with many buildings that do not meet modern seismic standards. In the affected cities (e.g., Kahramanmaraş/Marash, Türkoğlu, Nurdağı, İslahiye) the 2023 event caused widespread building collapse, displacement and strain on emergency response. The lack of rapid, accurate building-level damage data hampered immediate prioritisation of search & rescue and subsequent reconstruction planning.

Technical approach and data

- Pre-event and post-event satellite imagery: Planet Labs 50 cm, Maxar 30 cm.
- Building footprints from sources such as Microsoft / OpenStreetMap (used as baseline geometry).

13 Sources

- Robinson, C., Gupta, R., Nsutezo, S. F., Pound, E., Ortiz, A., Rosa, M., White, K., Dodhia, R., Zolli, A., Birge, C., & Lavista Ferres, J. M. (2023, February). *Turkey Earthquake Report (MSR-TR-2023-7)*. Microsoft Research
- "Microsoft/Planet Webinar: Natural Disaster Management - Using AI for Rapid Building Damage Assessment." Planet Labs. learn.planet.com
- Microsoft GitHub repository: "building-damage-assessment" toolkit. GitHub
- Yu, X., Hu, X., Song, Y., Xu, S., et al. (2024). "Intelligent assessment of building damage of 2023 Turkey-Syria Earthquake by multiple remote sensing approaches." *npj Natural Hazards*.

- Pre-training of CNNs on the xBD dataset (a global building-damage dataset) and then fine-tuning to the Turkish context using the open-source satellite imagery labeling tool.
- Semantic segmentation of imagery: classify pixels into damaged/undamaged/background. Then aggregate to building-level damage.
- Integration with population estimates (e.g., WorldPop population estimates) to estimate number of people affected (though this step may be inferred rather than deeply described in the published report).
- Rapid workflow: results delivered to national emergency agency AFAD within ~3 days of the event.

Scalability

The methodology demonstrated significant scalability, with its application across multiple cities in disaster-prone regions. The use of open-source tools and pre-trained models enables adaptation to different types of disasters and geographic areas. Leveraging global datasets, such as Microsoft's building footprints and WorldPop population data, suggests a potential for the worldwide application.

Impact

The GeoAI-based building damage assessment carried out after the February 6, 2023, earthquake in Turkey delivered a rapid, data-driven understanding of urban destruction across multiple cities, including Kahramanmaraş, Türkoğlu, Nurdağı, and Islahiye. Within just three days, Microsoft Research and its partners produced detailed building-level damage maps derived from satellite imagery and convolutional neural networks (CNNs). These analyses identified approximately 3,849 damaged or destroyed buildings and an estimated 160,000 affected residents. The outputs were provided directly to Turkey's Disaster and Emergency Management Presidency (AFAD), enabling authorities to prioritise emergency response, allocate rescue resources, and plan for temporary shelter and reconstruction. The integration of GeoAI methods with high-resolution imagery substantially accelerated situational awareness compared to traditional field surveys, demonstrating how artificial intelligence can complement human decision-making during crises. Beyond the immediate emergency, the project also showcased how scalable, reproducible GeoAI pipelines can strengthen long-term disaster preparedness and resilience planning in earthquake-prone regions.

Challenges and lessons learned

The Turkey Building Damage Assessment project faced challenges related to data quality, model accuracy, and operational coordination. Rubble extending beyond building footprints and outdated footprint datasets led to underestimation of damage, while variations in satellite imagery quality and dense urban layouts made it difficult for convolutional neural networks to distinguish adjacent structures. Estimating affected populations using gridded data also introduced uncertainty, and coordinating among Microsoft Research, satellite providers, and AFAD under tight timeframes required strong logistical management. Despite these issues, key lessons emerged: pre-trained GeoAI models on global datasets can be rapidly adapted to local contexts for accurate, scalable assessments; open data and tools enhance transparency and collaboration; and human validation of AI outputs ensures reliability. The project demonstrated that pre-established partnerships, open-source technologies, and AI-human collaboration are essential to delivering rapid, actionable insights for disaster response and building long-term resilience in earthquake-prone regions.

10. AI-powered vulnerability map for enhancing climate resilience (Barcelona, Spain)

Key application area: Urban planning, climate adaptation planning,

Title: ClimateReady Barcelona- AI-powered vulnerability map for enhancing the climate resilience of Barcelona

City/Region: Barcelona, Catalonia, Spain

Image: Screenshot of Climate Vulnerability Map of Barcelona, source: Climate Ready Barcelona **project UI**

Brief description

The Climate Vulnerability Map of Barcelona is an interactive geospatial analysis tool designed to identify buildings most at risk during extreme heat events. It evaluates over 61,000 residential buildings across the city using a multi-factor Climate Vulnerability Index (CVI) derived from socio-economic, demographic, climatic, infrastructural, health, energy, and building-characteristic indicators. The tool combines real data with simulated data through a hybrid AI methodology. It offers a user-friendly GIS interface that allows users to explore more than fifty indicators individually, visualise temporal changes, and generate customised vulnerability indices by adjusting indicator weights. Additionally, the application features a dedicated module that allows users to locate climate shelters available in the city based on date, time, and specific desired features.

Urban challenge addressed

Barcelona is increasingly exposed to more frequent and intense heat waves due to climate change, disproportionately affecting vulnerable populations and buildings with poor resilience. This tool responds to the urgent need for precise, building-level intelligence to support climate adaptation, energy poverty mitigation, and public health preparedness. By spatially identifying vulnerable buildings, the map enables evidence-based decision-making for urban planning and protective actions, enhancing the city's capacity to safeguard citizens during extreme heat events.

Technical approach and data

The tool is built entirely on data sourced from public open-data portals, ensuring transparency, reproducibility, and alignment with open-government principles. All data is harmonised, structured and interconnected through the BIGG Ontology, which forms the conceptual and technical backbone of the solution. This ontology enables the integration of heterogeneous datasets, allowing climatic, socio-economic, demographic, infrastructural, health, energy and building-related information to be merged coherently despite originating from different sources and formats.

Because not all indicators are available for every building, the methodology relies on advanced data integration techniques that can handle multiple levels of spatial and temporal granularity. The system accommodates datasets ranging from metropolitan-scale climate layers to neighbourhood socio-economic statistics and detailed cadastral records at the parcel or building level. Graph Neural Networks are particularly valuable in this process, as they allow the model to learn from spatial relationships and infer missing information across the urban fabric. By leveraging the structure of the city (buildings, their proximity, and their shared characteristics), neural networks help fill data gaps and generate accurate estimations for buildings lacking complete datasets.

The resulting dataset for each building incorporates a broad range of indicators that can be analysed through the map, including temperature trends, precipitation patterns, vegetation cover, energy-consumption behaviours and indoor temperature measurements, as well as building-specific attributes such as age, typology, size, and structural characteristics. Additional layers capture socio-demographic and socio-economic information such as gender, age, income, migration status, housing costs, and proximity to essential services.

Scalability

The tool was conceived as an interoperable and scalable platform, designed to be easily replicated in other cities and regions. Its modular architecture, data-driven design, and adaptable indicator framework allow seamless integration of region-specific datasets, while the AI-based methodology can be retrained or recalibrated for new geographic contexts. Because the majority of the datasets used, such as cadastral information, socio-economic variables, and demographic indicators, are available through national open-data portals, scaling the map to cover the whole of Spain would not pose significant technical difficulties. Most of the core data sources already exist for all Spanish regions, allowing the methodology to be extended with minimal adjustments.

Nevertheless, particular attention must be paid to identifying and assessing additional or region-specific datasets that may vary across the territory, especially those related to infrastructure or public services. A similar consideration applies when replicating the tool beyond Spain: the underlying framework can be easily transferred to other countries, but the availability, quality, and granularity of local datasets remain essential prerequisites for generating a robust Climate Vulnerability Map.

Impact and benefits

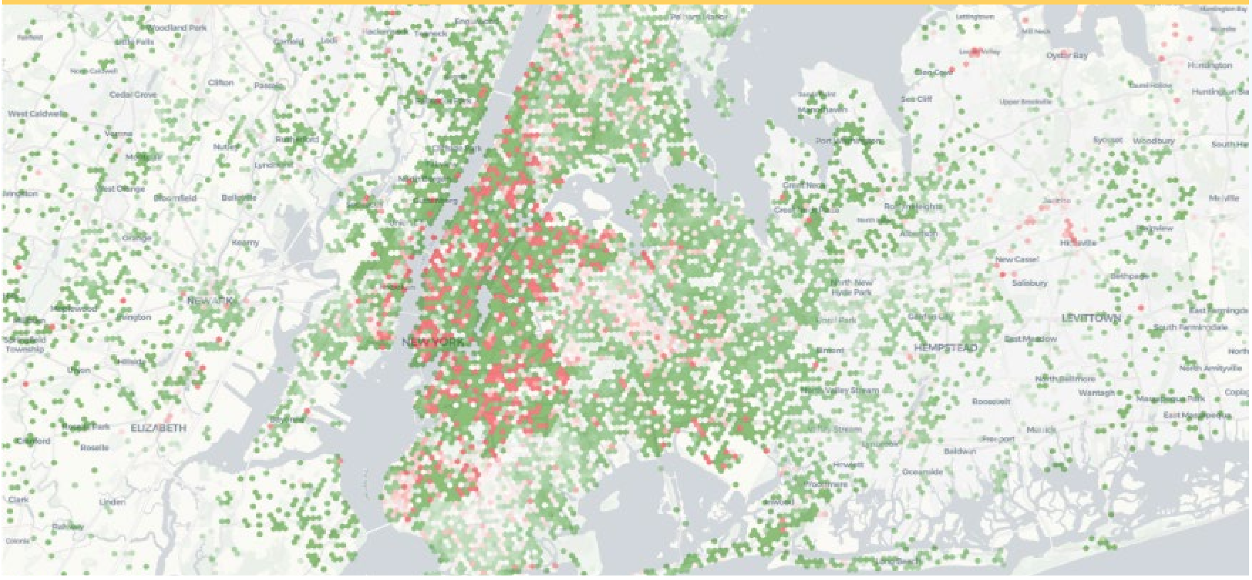
The Climate Vulnerability Map provides significant value to a wide range of stakeholders by enabling a deeper and more precise understanding of heat-related risks across the urban landscape. For policymakers, it offers a robust evidence base to support climate-adaptation strategies, land-use planning, and the prioritisation of interventions in areas where vulnerability is highest. Public administrations responsible for energy and social services can utilise the tool to more effectively target assistance to households experiencing energy poverty or inadequate thermal comfort, thereby enhancing the efficiency and fairness of support programmes. Researchers and urban planners benefit from an unprecedented level of spatial detail, enabling more advanced analyses of the interactions between climate dynamics, the built environment, and socio-economic conditions. The tool also empowers the general public by increasing awareness of climate risks and, through its integration with La Meva Energia, provides personalised climate-related communications that help vulnerable residents understand their own exposure and potential protective measures.

Challenges and lessons learned

The development of the tool involved addressing several challenges, particularly related to integrating heterogeneous datasets with varying levels of spatial and temporal granularity. Ensuring consistency across climatic variables, socio-economic statistics, cadastral information, and energy data required a robust data architecture. Another key challenge was the uneven availability of data across buildings and districts, which necessitated the use of advanced AI techniques such as Graph Neural Networks to infer missing values and maintain accuracy in the vulnerability estimations. Creating a tool that could serve both expert users and the general public also posed difficulties, as it required an interface that is intuitive and accessible while still offering advanced analytical capabilities, customisable weighting schemes, and multi-layer exploration. Finally, adapting the methodology to be scalable across different regions highlighted the importance of evaluating the quality and availability of local datasets, as the transferability of the tool depends heavily on accessible and reliable data inputs.Throughout the process, an essential lesson learned was that close collaboration between technical teams, municipal departments, and local stakeholders is fundamental to ensure that the tool addresses real urban needs and remains grounded in practical decision-making contexts.

11. Forecasting Ride-Hailing Demand with Geo-Embeddings[14]

Key application area: Urban mobility and transport optimisation
City: New York City, USA



Improvements on predicting high resolution Uber demands on with our Globeholder geo-embedding backed ML pipeline, built in minutes on the no-code platform, source: Globeholder

Brief Description

Developed by Globeholder, this GeoAI solution uses geospatial foundation models and geo-embeddings to accurately forecast ride-hailing demand across New York City. By encoding each location's unique spatial "DNA," the model enables high-resolution, dynamic demand forecasting that enhances urban mobility planning, reduces congestion, and improves transport system efficiency.

Urban challenge addressed

Forecasting ride-hailing demand in a complex metropolis like New York City is difficult due to diverse and interdependent spatial factors-transit hubs, land-use patterns, events, and socioeconomic dynamics. Traditional ML approaches rely on manual feature engineering and fail to generalize across boroughs, resulting in low accuracy and limited operational value.

Technical approach and data

- **Technical approach:** *Geospatial Foundation Model* with geo-embeddings
- **Data Inputs**: Historical Uber pickup data, street networks, zoning maps, points of interest, parking availability, and socioeconomic datasets
- **Method:** Each location was transformed into a geo-embedding vector that captures spatial context ("location DNA"). These embeddings were combined with temporal and event-based features in a no-code ML pipeline to forecast ride-hailing demand.

14 Sources:

- Expert consultation
- Globeholder (2025). *Forecasting Ride-Hailing Demand in New York City – Use Case.* Retrieved from https://globeholder.ai/use-cases
- Globeholder (2025). *Revolutionizing the Future of Locational Intelligence with Globeholder's Geospatial Foundation Models.*

Scalability

The solution is highly scalable and adaptable to other cities and mobility platforms. Once trained, the geo-embedding model can be transferred across regions with minimal calibration, supporting large-scale deployment and integration with smart city and digital twin systems.

Impact

The approach achieved a **+44% improvement in prediction accuracy** compared to traditional machine learning methods, significantly enhancing resource allocation and reducing idle vehicle time. The system enables planners and mobility operators to anticipate demand surges, optimize fleet deployment, and reduce congestion and emissions, generating both economic and environmental benefits.

Challenges and lessons learned

Implementing the GeoAI solution in New York City revealed several challenges, including the need to harmonize diverse data sources, ensure consistent data quality, and manage the high computational demands of large-scale urban datasets. Another key difficulty was translating complex model behavior and outputs into insights understandable to non-technical users such as planners and policy makers. Despite these hurdles, the project demonstrated that embedding spatial context directly into machine learning pipelines substantially improves predictive accuracy, while integrating GeoAI into no-code environments accelerates model deployment and strengthens decision-support for real-time urban mobility management.

12. GeoAI+ Data-driven visual planning of smart park and digital twin city project (Hefei, China)[15]

Key Application Areas: Smart park planning and management, digital twin city, Urban operation and services
Title: GeoAI+ Data-driven visual planning of smart park and digital twin city project (Hefei, China)
City/Region: Luogang Park, Hefei, China

Digital twin platform and smart application in the Luogang park smart projects Source: Luogang Park Construction Enterprise

Brief description of the tool

The Digital twin platform of Luogang park has built the country's largest park-level integrated above-ground and underground full-scenario digital twin map used in GeoAI and 3D map, realizing centimeter-level virtual mapping of the park's terrain, buildings, facilities, vegetation, etc. It provides visual data support for the sustainable optimization and innovation of park planning, management and services. Participants in the smart park of Luogang Park include park construction enterprises (Hefei binhu new area construction investment Co., Ltd.,China), design enterprises (China Smart City Planning & Design Research Institute Co., Ltd., Smart City (Hefei) Standardization Research Institute Co., Ltd.), and data platform development enterprises (Iflytek Zhiyuan Information Technology Co., Ltd.,and Anhui Zhongke Xinchuang Integrated Services Co., Ltd.). The platform takes UAV aerial modeling as an important data source, supplemented by AI modeling for detailed optimization and supplementation.

15 Sources
- Luogang Park Baidu Encyclopedia
- Economic Network Blog
- Hefei Evening News

Urban challenge addressed

Luogang Park is the host site of the 14th China (Hefei) International Garden Expo, with a planned total area of 12.7 square kilometers. Before its opening, it was expected that during the three-month exhibition period, the park would receive a total of 5 million to 10 million domestic and foreign tourists, and the single-day passenger flow on October 1 was expected to exceed 400,000. Facing such a huge passenger flow and vehicle flow, the operation and management of Luogang Park are facing enormous challenges. By integrating the infrastructure and sensors in the park, the digital twin platform helps the park operators grasp the real-time dynamics of the park, ensure the park's safety, and improve the park's service and management capabilities.

Technical approach and data

The 3D visualization model of the digital twin platform is constructed by using UAV aerial photography to collect high-precision surveying and mapping data, combined with the geographic information of the GIS system and professional visual rendering technology, also used on CIM(city information modelling) with ISO 37156. The 3D model of the platform covers various types of park elements, including 91.3 kilometers of roads, 1 square kilometer of water systems, 2 bridges, 7 buildings, 199 types and 114,000 plants, green spaces accounting for about 90% of the park's planned area, and 124 kilometers of underground pipelines. The platform carries real-time monitoring data from more than 15,000 perception devices in the park, realizing all-round and refined management of the park.

Impact and benefits

The platform has created the largest "Plant Basic Database" in Anhui Province, built an all-space unmanned control system, and connected 6 major departments of Hefei Municipality, including public security, transportation, fire protection, housing and urban-rural development, medical care, and emergency response. The park has safely and conveniently received more than 26.766 million tourists (from September 26, 2023 to September 26, 2025), with the highest single-day passenger flow reaching 420,000. Due to its outstanding performance in tourist services, safety management and intelligent operation, the park has been recognized by tourists and ranked among the "Top 20 Domestic Popular Tourist Destinations" during the National Day holiday in 2023.

Scalability

Digital twin technology is widely used in smart city construction in China. According to the data from the Ministry of Housing and Urban-Rural Development of the People's Republic of China, more than 100 cities across the country have built or are building urban information model platforms. Among them, Xiongan New Area, Nanjing, Foshan and other cities have achieved remarkable application results. Xiongan New Area adheres to the simultaneous planning and construction of digital cities and real cities, and has built a sound data infrastructure. Nanjing and Foshan have promoted the in-depth application of digital twin technology in urban management by building intelligent infrastructure, especially the large-scale application of UAV inspection in the fields of ecology, transportation, and construction, and have achieved good results in urban visual planning and management.

Challenges and lessons learned

Key challenges include:

- Difficulties in realizing cross-departmental data sharing: The platform has connected 6 major departments of Hefei Municipality, including public security, transportation, and fire protection. However, there are differences in data standards and interface protocols among various departments, and additional resources are required for data format conversion and adaptation.

- High demand for computing resources: The platform covers scenarios such as parallel rendering of full-element digital twin models, real-time inference of multiple AI algorithms, and high-frequency processing of data from 10,000-level sensors. Especially during the peak passenger flow period on holidays, the computing load increases sharply, which puts forward extremely high requirements for high-performance computing support.

- Large number of models and prominent bearing pressure: It is necessary to build dozens of types of subdivided digital twin models such as vegetation, buildings, facilities, and pipelines. The total number of models is large and requires 1:1 high-precision restoration. Parallel loading and real-time synchronization of multi-format models are prone to freezes and delays.

Lessons learned:

- Deepening local multi-subject collaboration is the core prerequisite for the platform's implementation. The strong collaboration of multiple departments such as municipal administration, landscape architecture, and transportation, as well as operators and service providers, can ensure that data is in line with scenarios, models are adapted to needs, application rights and responsibilities are clarified, collaboration barriers are reduced, and construction and operation efficiency is improved.

- Consolidating the basic support capacity determines the platform's operation effect. Reliable multi-source data, sufficient computing infrastructure, and a professional technical team are the keys to the stable deployment, efficient operation of the platform, and accurate and timely output of results.

- Cultivating local technical operation and maintenance capabilities is the core of long-term sustainability. Through special training and technical guidance to improve the digital skills of the park operation team and cultivate local operation and maintenance talents instead of relying on external service providers, the long-term stable operation of the platform and the continuous iteration of functions can be ensured.

Annex II. GeoAI tools, platforms & resources

This annex complements *the step-by-step guidance (step 2.4 GeoAI Solution Development or Procurement*) by providing examples of GeoAI tools and platforms that municipalities can consider when deciding whether to purchase, co-develop, or build GeoAI solutions in-house. The listed tools and platforms represent a range of proprietary and open-source options, supporting different levels of technical capacity, budgets, and urban needs.

GeoAI Tool / Platform	Open-soruce / Licensing / Pricing	Datasets Used / Supported	GeoAI application areas (examples)	Key Resources / Links
Aino (QGIS Plugin)	Open-source/Free	OpenStreetMap (via natural language prompts), QGIS datasets	• Land-use planning, housing & infrastructure • Mobility • Environmental monitoring • Disaster management	• Aino Plugin • qGIS training manual • Advanced QGIS Analysis with AI and Machine Learning
AI Georeferencer (Mundi)	Proprietary Free basic / Paid Pro	Uploaded aerial/satellite/scanned imagery	• Land-use planning & housing • Mobility • Climate resilience • Disaster management • Governance	• Mundi Georeferencer
ArcGIS Pro (ESRI)	Proprietary/ Paid licenses (Creator / Professional / Academic)	ESRI Living Atlas, Sentinel, Landsat, user-uploaded GIS & tabular data	• Land-use planning & housing • Mobility • Disaster management • Energy • Governance	• ArcGIS GeoAI Toolbox • ESRI Academy • ArcGIS Blog
BEAM (UNITAC)	Open-source/Free	High-resolution aerial and satellite imagery (e.g., commercial or open providers) Outputs: building footprints extracted as shapefiles or geospatial layers	• Land-use planning housing and infrastructure	• BEAM main page • BEAM user manual
CARTO	Proprietary (SaaS) / Subscription	Google BigQuery, Snowflake, Databricks, PostGIS, open data APIs	• Land use planning, housing & infrastructure • Mobility • Energy • Environmental and climate resilience • Governance	• CARTO
City AI Engine (People+ AI)	Open data platform/ Free	Open urban datasets (India Smart Cities Mission)	• Governance • Land-use planning, housing and infrastructure	• City AI Engine
CityGML	Open standard (OGC)/ Free	Any 3D GIS datasets, CAD/BIM models, CityJSON, LiDAR	• Land-use planning & infrastructure • Mobility • Energy • Climate resilience	• OGC CityGML • 3DCityDB
CVAT	Open source (MIT)/ Free core / Paid hosted plans	User-uploaded imagery, drone and satellite data, COCO/YOLO/VOC formats	• Land-use planning, housing and infrastructure • Waste management • Public safety • Disaster management	• CVAT Docs • GitHub
Destination Earth (DestinE)	Public / EU-funded/ Free access	Copernicus Sentinel, ECMWF reanalysis, EUMETSAT, climate simulations	• Climate resilience & disaster management	• DestinE Platform • Destination Earth

GeoAI Tool / Platform	Open-soruce / Licensing / Pricing	Datasets Used / Supported	GeoAI application areas (examples)	Key Resources / Links
DTN	Proprietary/ Subscription	Satellite, Earth observation, and real-time weather datasets (e.g., radar, lightning, forecasts, climate models)	• Energy • Mobility • Environmental monitoring • Disaster preparedness	• DTN
Digital Blue Foam (DBF)	Proprietary/ Subscription	OpenStreetMap, Copernicus, custom GIS & BIM data	• Land-use & housing • Energy • Climate resilience	• Digital Blue Foam • 15-Minute City Whitepaper
FlyPix AI	Proprietary/ Subscription	Drone imagery, Sentinel, Landsat, user-supplied datasets	• Land-use planning & housing • Waste management • Environmental monitoring	• FlyPix AI
GEOVIA (Dassault Systèmes)	Proprietary/ Paid services	Proprietary geoscience & simulation datasets, CAD/BIM data	• Land-use planning & infrastructure • Energy • Climate resilience	• GEOVIA
GeoAI (Python package)	Open source/ Free	Sentinel, Landsat, NAIP, Overture Maps, user-supplied datasets	• Land-use planning & housing Environmental & climate resilience • Disaster management • Waste management	• opengeoai.org • GitHub
GeoRetina AI (GRAI)	Proprietary / Free trial / Pro / Enterprise plans	Sentinel, Landsat, Google Earth Engine, user-uploaded vector & raster data	• Land-use planning & housing • Energy • Environmental & climate resilience • Governance	• GeoRetina
Globeholder AI	Proprietary / Subscription	Global geo-embeddings, proprietary AI geospatial data	• Land-use planning & housing Mobility • Energy • Governance	• Globeholder AI
Google AlphaEarth Foundations (DeepMind)	Proprietary / research model/ Free (via Google Earth Engine)	Global satellite embeddings (optical, radar, LiDAR, climate models)	• Land-use planning & housing Water management • Climate & environmental resilience • Energy	• DeepMind Blog • Earth Engine Dataset
Green City Watch (TreeTect)	Open-source initiative/ Free	Sentinel-2, Copernicus, open ecological & vegetation datasets	• Environmental & climate resilience • Land use planning, housing and infrastructure • Public health	• ESA • Copernicus Masters
Heli AI	Proprietary / Subscription	User-uploaded GIS data, raster and vector layers	• Land-use planning, housing & infrastructure • Mobility • Energy	• Heliware AI
InflowGo	Proprietary / Subscription	Hydrological & drainage datasets, municipal stormwater data	• Water management • Disaster management • Infrastructure optimisation	• InflowGo
QGIS	Open source/Free	OpenStreetMap, Copernicus Sentinel, Landsat, Natural Earth, user-provided spatial data	• Land-use planning, housing & infrastructure • Environmental management & resilience • Waste management • Disaster management	• QGIS Docs • QGIS Tutorials
WebGIS Urban Sprawl Information System (USIS)	Public /Free	LISS-4 satellite data (India), national GIS datasets	• Land-use planning & housing • Urban growth monitoring • Governance	• VEDAS Urban Portal

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