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Article

Gate4EcoAI: A Digital Platform with Initiatives from World-Leading Smart Sustainable Cities (Part 1: Urban Water Management)

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Abstract

Environmental planning is essential for climate action, as cities face air pollution, flooding, drought, and other environmental stresses. Yet research on these challenges remains limited in the state of Amazonas, Brazil. Building on a prior participatory study of 1,242 residents, this article advances a long-term research agenda focused on urban water management. The study pursues three goals: update, identify, and classify Benchmark Smart Sustainable Cities (BSSCs), with priority given to the Gold tier (GBSSCs); map ECO AI and Non-AI initiatives, AI techniques, and digital enablers used by GBSSCs to address urban water challenges (Manaus main concern); propose and disseminate Gate4EcoAI, an interactive platform with GBSSCs' urban water initiatives. This applied research triangulated ten international city rankings using a mixed-methods approach (systematic literature review, bibliometric and documentary analyses, statistical methods, open-science practices, and AI-assisted tools) to collect, clean, analyze, and visualize data. Of 265 cities assessed, 99 were classified as BSSCs (20 as Gold). GBSSCs applied 76 regulatory instruments and adopted at least 243 distinct initiatives to address water challenges. Gate4EcoAI is a multidimensional, queryable evidence-to-policy bridge, with valuable initiatives to support the development of roadmaps for urban water challenges. By linking proven initiative types (e.g., Network Process Control, Quality Monitoring), dominant AI techniques (ML-Anomaly Detection, Supervised ML), and enablers (IoT, Cloud) to real-world statuses, it empowers AI developers, policymakers, utilities, and researchers with evidence-based benchmarking to adapt the best practices locally. For Manaus and analog cities, this structured knowledge base bridges science-to-policy gaps, accelerating resilient water governance amid Amazonian vulnerabilities.

Keywords: AI; Benchmark Smart Sustainable Cities; Environmental Planning; ECO AI Initiatives

1. Introduction

1.1. Human Challenges and Publication Gaps in the Amazon Region

We face global risks that could push our planet past a point of no return (Aengenheyster et al., 2018; IPCC, 2022a). Among Earth's critical ecosystems, the Amazon rainforest is vital to planetary stability (Lenton et al., 2008; Malhi et al., 2008; Steffen et al., 2018; Lovejoy and Nobre, 2019; Meineke, 2024; Finer et al., 2025). Relentless deforestation and climate change are pushing the Amazon toward a tipping point of savannization, a process that disrupts evapotranspiration, reduces moisture recycling, lengthens dry seasons, and triggers self-reinforcing droughts that convert forest to savanna. Once crossed, this threshold could generate an irreversible cycle of forest loss, carbon emissions, and diminished rainfall (Cox et al., 2000; Lovejoy and Nobre, 2019; Armstrong McKay et al., 2022; Flores et al., 2024).

Two bibliometric reports, openly accessible via persistent links (Gomes da Silva, 2025c, 2025d), reveal significant publication gaps concerning the Amazon and its cities. The first report, focused on the "Amazon Region," identified nearly 908 publications featuring this term in titles and abstracts, spanning articles, conference proceedings, book chapters, reports, books, and dissertations. Field-specific analysis shows limited attention to Sustainability, Environmental Planning, and Environmental Resource Management (Figure 1).

A second report on "Manaus", the Amazon capital, identified 3,868 publications primarily concentrated in Humanities, Geography, Medicine, and Sociology, with minimal coverage of Environmental Planning and Environmental Protection. Together, these reports indicate that research on **Sustainability** and **Environmental Planning** in the Brazilian Amazon remains underdeveloped. These gaps are especially pronounced in Manaus, where long-term environmental planning is absent, and the Smart City agenda has failed to move beyond political rhetoric.

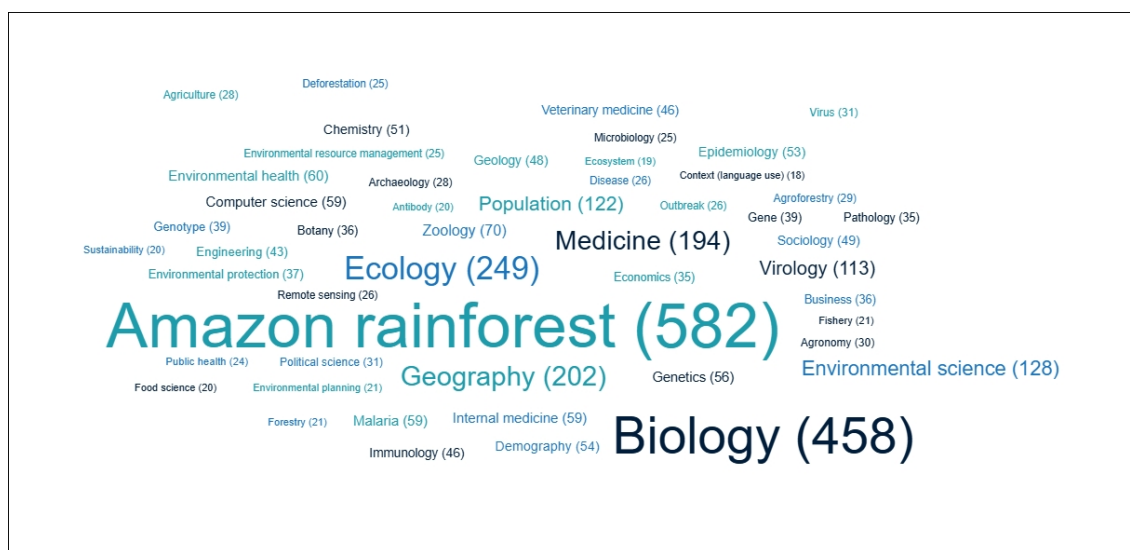


Figure 1. Fields of study related to the Amazon Region.

1.2. Long-Term Agenda, Goals, and Research Questions.

To address these gaps, the author has maintained a long-term research agenda since 2022. As part of this effort, Da Silva (2023) surveyed 1,242 Manaus residents and found: (i) among 17 environmental problems, the five most critical are increased stream/river pollution, increased street garbage, insufficient urban afforestation, increased air pollution, and increased traffic congestion; (ii) citizen participation in co-creating solutions remains very low, as public administrations have not effectively engaged citizens in urban planning; (iii) two models (the P⁵ model and the Citizen Engagement Kit) with 120 approaches drawn from top smart cities could address these problems. However, that study did not examine smart sustainable city initiatives for urban water management, Manaus's primary environmental challenge.

This complementary research advances the agenda through three goals: **G1:** Update, identify, and classify BSSCs, prioritizing the Gold tier (GBSSCs); **G2:** Map ECO AI/Non-AI initiatives, AI techniques, and digital enablers used by GBSSCs to address urban water challenges; **G3:** Propose and disseminate Gate4EcoAI, an interactive platform showcasing GBSSCs' urban water initiatives.

Five corresponding questions guide this study: (Q1) Which cities are consistently recognized as GBSSCs across international rankings? (Q2) What ECO AI and Non-AI initiatives have GBSSCs implemented to address urban water challenges? (Q3) What AI techniques predominate in GBSSCs for urban water management? (Q4) Which digital enablers facilitate smart water solutions in globally recognized cities? (Q5) How can Gate4EcoAI support evidence-based benchmarking and policy transfer for Manaus and similar cities?

1.3. Importance and Originality

Water is crucial for life, and Brazil holds 12% of global freshwater resources, with 18.3 million hectares of water surface; the Amazon biome contains the majority (11,319 Mha; 62%) (Atuhaire, 2025; MapBiomias, 2024). Despite this abundance, Manaus ranks poorly in national sanitation metrics, placing 86th out of 100 major Brazilian cities and scoring 4.55/10 (Instituto Trata Brasil, 2024), with consistent presence in the bottom 20 municipalities over the past decade, a striking paradox given its 99.49% water-supply coverage.

This article makes four original contributions. First, it advances a long-term, citizen-grounded research agenda on how world-leading cities address urban environmental challenges, anchored in the real priorities of 1,242 Manaus residents. Second, it introduces a novel percentile-based BSSC index derived from the summary statistics of ten rankings. Unlike Principal Component Analysis approaches (Abdi and Williams, 2010; Jolliffe and Cadima, 2016; Rađenović and Boshkov, 2023), this offers a simpler, more reproducible framework aligned with OECD/EU/EC-JRC (2008) guidelines. Third, it formally defines ECO AI Initiatives, a new concept that redirects AI governance discourse from AI's own environmental footprint toward AI's role in solving citizens' daily environmental problems. Fourth, it delivers Gate4EcoAI: the first openly accessible benchmarking platform built from world-leading cities and calibrated to the environmental priorities of an Amazonian city.

2. Literature Review

2.1. The Imperative to Modernize Urban Management

Extreme weather events, rising sea levels, and the spread of infectious diseases exemplify the threats driven by human activities and climate change (McSweeney and Tandon, 2024; Microbe, 2021; Strauss et al., 2021).

For decades, several scientists have been alerting us about the need to change our way of living in the city. One good example comes from the planetary boundaries framework (Johan Rockström et al., 2009), which defines nine critical Earth-system processes necessary for a stable planet. In 2009, three boundaries had already been transgressed; by 2023, six. The 2025 report by Planetary Boundaries Science confirmed that seven of the nine planetary boundaries have now been exceeded (Figure 2), with only stratospheric ozone depletion remaining securely within the safe zone.

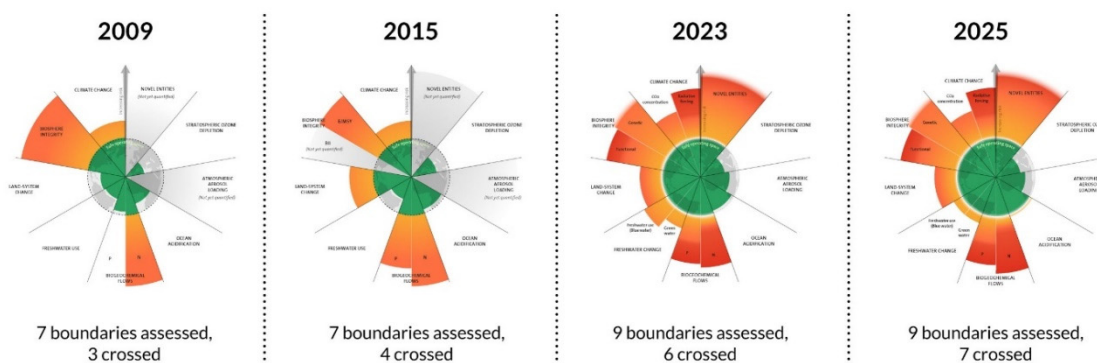


Figure 2. Evolution of the planetary boundaries over time.

Climate change is identified as the most urgent boundary, driving long-term shifts in weather patterns and amplifying extreme events with cascading effects on ecosystems and societies (Planetary Boundaries Science, 2025). In addition, another challenge is the growth of the global population, which is expected to peak at roughly 10.3 billion in the mid-2080s before gradually declining (UN DESA, 2024), which is further intensifying pressure on urban systems.

In this context, modernizing and improving urban management is essential, as cities occupy only 2% of Earth's land but consume approximately two-thirds of global energy and account for about 75% of carbon emissions (World Bank Group, 2021).

2.2 Manaus in Context

Manaus, capital of Brazil's largest state, Amazonas, spanning more than six times the area of the United Kingdom, is home to over 2.3 million of the state's approximately 4.3 million residents (IBGE, 2025). Founded on 24 October 1669, the city experienced two rubber booms (1879–1912; 1942–1945) and later became an industrial hub after the creation of the Manaus Free Trade Zone in 1957, which attracted over 600 companies.

A SWOT analysis of Manaus (Figure 3) highlights considerable strengths, its position at the heart of the Amazon, industrial capacity, and potential as an ecotourism and bioeconomy hub offering low-carbon solutions such as electric/hybrid boats, digital twins, smart water and waste systems, solar mini-grids, and IoT-managed energy systems. On the other hand, the city has serious weaknesses and threats. Despite having Brazil's fifth-largest municipal GDP in 2021 (IBGE, 2023), Manaus was ranked the 9th-worst capital to live in (Wilm et al., 2024), scored 4.55/10 in national sanitation (Instituto Trata Brasil, 2024), placed 3,885th in Brazil's Sustainable Development Index (IDSC-BR, 2025), and faces rising environmental pressures including floods, droughts, untreated wastewater, rapid urban expansion, and deforestation (Rico et al., 2021; Espinoza et al., 2022; Silva et al., 2022). Future growth simulations (Santos et al., 2022) underscore the urgency of sustainable planning along the BR-319 corridor.

Without a strategic shift toward smart, sustainable solutions and stronger global engagement, Manaus risks missing its opportunity to become a model of green, inclusive tropical growth.

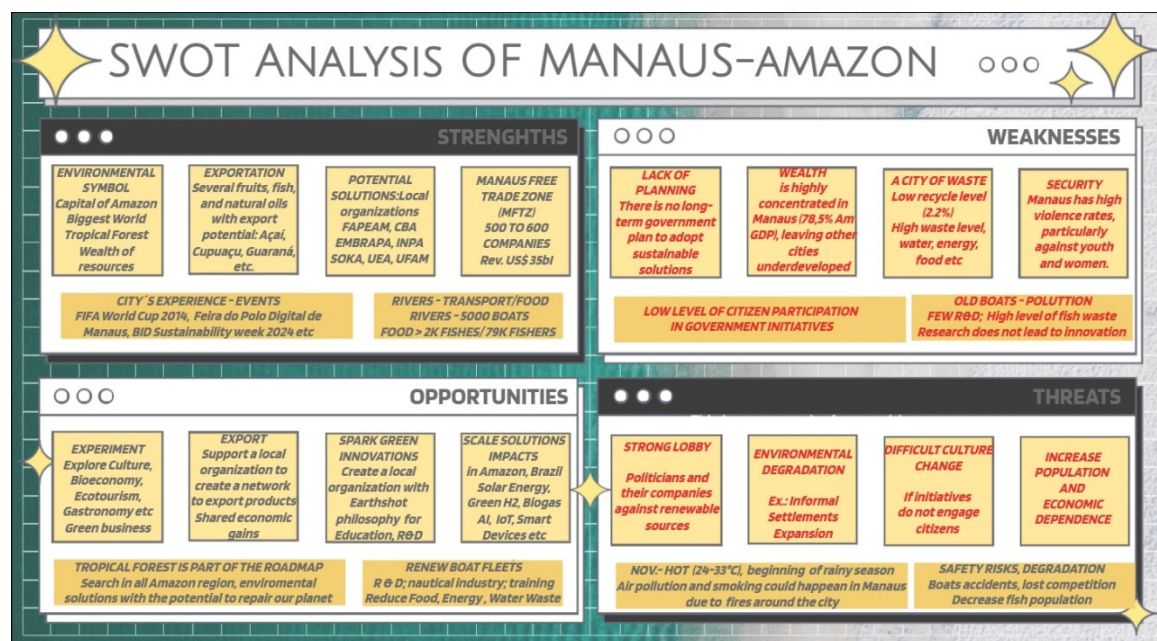


Figure 3. SWOT Analysis of the Brazilian Amazon Capital (Source: Author).

2.3. Global Initiatives and International Cooperation

Various global initiatives (Figure 4) have emerged to modernize cities and address climate change. The Paris Agreement (UN, 2016) establishes a global framework for nationally determined climate targets (NDCs). The World Bank's GovTech Agenda supports digital governance innovations in 147 countries, with 1,449 projects as of October 2022 (Bharosa, 2022; World Bank, 2022).



Figure 4. Example of global initiatives to address climate change.

The ITU's United for Smart Sustainable Cities (U4SSC) initiative provides around 91 Key Performance Indicators to enable ICT-aligned sustainable urban development, having supported over 100 cities worldwide (ITU, 2022; Reinar, 2025).

Other notable programs include C40 Cities, the Net Zero Cities initiative, the NetZero Tracker, the UN's Race to Zero campaign, the Earthshot Prize, and the Global Platform for Sustainable Cities (GPSC, n.d.). As the IEA, IRENA, and UN Climate Change High-Level Champions (2022) emphasize, coordinated international cooperation is essential to accelerate clean energy innovation and adoption by 2030.

2.4. Smart Sustainable Cities

Smart City and Sustainable City are among the most-cited urban terms across five scientific databases (Da Silva, 2023, pp. 14-17). Although approximately 87 publications address "smart city definition" in their titles and abstracts (Gomes da Silva, 2025e), this study does not review or discuss definitions of these terms. For this purpose, readers may consult Albino et al. (2015), Meijer and Bolívar (2016), Bibri and Krogstie (2017), and Nikitas et al. (2020).

Instead, two definitions were selected to align with the research objectives. The first comes from the Smart Cities Readiness Guide published by the Smart Cities Council (2015), which states, "A smart city uses ICT to make life better, work better, and be more sustainable".

The second encompasses Smart Sustainable City from ITU (2014), defined as "An innovative city that uses ICTs and other means to improve quality of life, efficiency of urban operation and services, and competitiveness, while ensuring that it meets the needs of present and future generations with respect to economic, social, environmental as well as cultural aspects."

Sustainability cannot be dissociated from Smart Cities efforts, since the UN's "New Urban Agenda" from 2019 states that smart cities should put people and their communities at the center of their plans. The goal is to use technology in a way that includes everyone. The end goal is to create societies that are safer, more resilient, sustainable, and truly inclusive. This is what Sustainable Development Goal 11 is all about (UNPAN, 2022, p. 6).

The IPCC Sixth Assessment Report highlights cities as central to both climate mitigation and adaptation, emphasizing that integrated urban planning, combining compact urban form, energy-efficient buildings, low-carbon transport, and green and blue infrastructure, can substantially reduce emissions while enhancing resilience (IPCC, 2022b).

In this context, smart cities and/or smart sustainable cities play a crucial role in mitigating and adapting to climate change. This role is supported by the World Bank Group's technical report (Patricio, 2023), which details how digital technologies like IoT automation in buildings (reducing cooling by two-thirds and heating by half), dynamic demand response, and distributed energy systems enable emissions reductions in buildings, transport, and waste sectors.

The role is also supported by scientific evidence, including Di Giulio et al. (2018), which highlights that smart city technologies are pivotal to effective urban climate governance, enabling cities like São Paulo to implement innovative policies and infrastructure to manage climate risks and emissions.

Findings from Fan et al. (2021) directly support the view that smart city policies are crucial for climate mitigation and adaptation. Using data from 230 Chinese cities (2005–2018), the authors show that implementing smart city pilot policies significantly improves low-carbon economic development and that this positive effect strengthens over time. Sotirios Karatzimas (2024) provides empirical evidence showing that smart city initiatives lead to measurable improvements in emissions reduction and climate resilience through enhanced reporting and targeted actions.

2.5. International Rankings Evaluating Cities

Over the past decade, several rankings have been developed to evaluate cities. Toh (2022) used six international rankings to support decision-makers, while Lai and Cole (2022) critically evaluated six smart city indices and found that the IESE Cities in Motion Index performed best overall. Da Silva (2023) used a different approach, employing five rankings, to identify 25 Benchmark Smart Cities. This study extends that approach to ten rankings (Figure 5), each offering a distinct yet related perspective on urban smartness and sustainability, combining quantitative and qualitative indicators across governance, technology, environment, and livability dimensions.

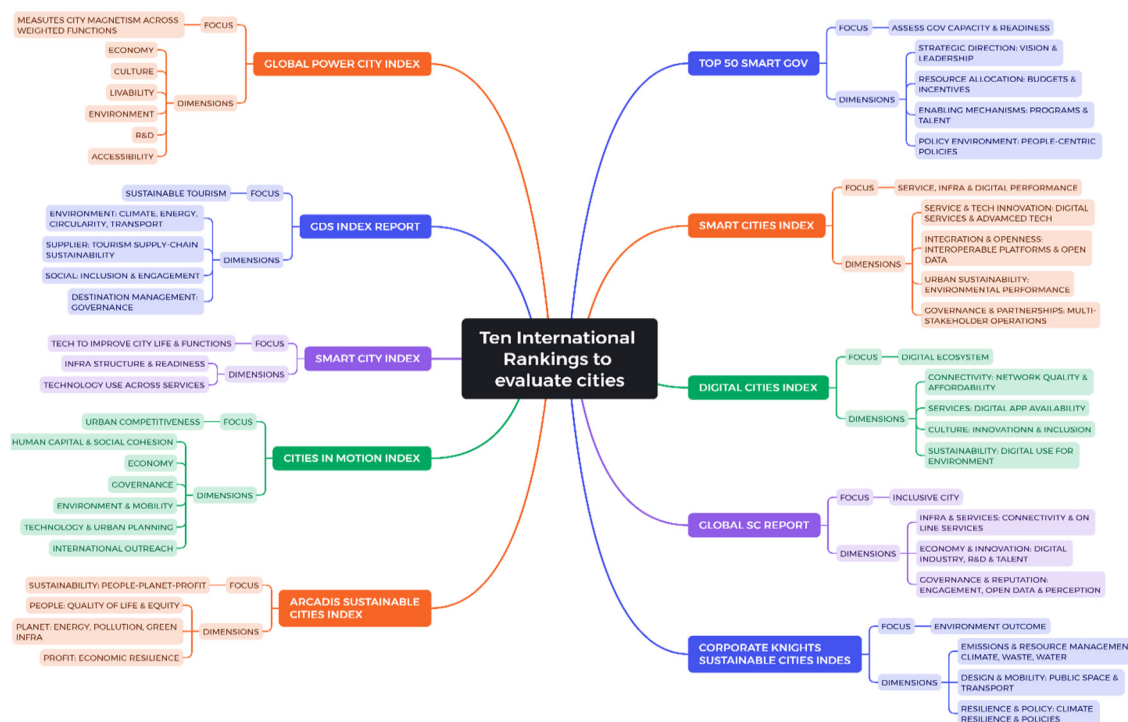


Figure 5. Ten international rankings used to evaluate and classify cities.

This study does not delve into how each index was created, how cities were selected, or how different factors were weighted. To avoid repetitive technical information, the reader can read Appendix A, which briefly summarizes each ranking and lists the top 10 cities.

Each ranking offers a distinct yet related perspective on what makes a city smart and sustainable, typically combining quantitative and qualitative indicators and incorporating input from experts and residents. In doing so, they capture not only urban infrastructure but also the everyday experience of city life.

These ten rankings help cities identify smart sustainability priorities by providing diagnostic frameworks across governance, technology, environment, and livability dimensions. However, cities should select rankings aligned with their local strategic goals rather than optimizing for all indices, using them as comparative reference tools to benchmark against peer cities and identify context-specific policy improvements rather than universal best practices.

2.6. Artificial Intelligence and ECO AI Initiatives

Since the seminal works of Hebb (1949) and Turing (1950), nearly 123,052 publications have explicitly used the term "Artificial Intelligence" in their titles and abstracts (Gomes da Silva, 2025b).

With the evolution of internet (from 1 to 10G), improvement of ICT infrastructures, and growth of investments of governments and tech giants, this field of study, since 2018, has expanded explosively in the scientific communities, with particularly intense activity in Computer Science (81K publications), AI-specific venues (73K), Medicine (26K), Psychology (26K), Engineering (25K), Political Science (16K), and Business (16K), while still relatively underexplored in areas such as Management (1.6K), Gene (1.6K), **Sustainability (1.6K)**, and **Environmental Science (1.7K)** (Gomes da Silva, 2025b), revealing both the breadth of AI's diffusion and the intriguing gaps where its transformative potential remains largely untapped.

When two terms focused on AI in Environmental Science are used, other bibliometric analyses reveal approximately 104 publications with "Green AI" in titles and abstracts, and 105 with "Sustainable AI" (Silva, 2025a; 2025b). Early works developed by Djefal (2018), Larsson et al., (2019), Schwartz et al. (2020), Asperti et al. (2021), Bjørlo et al. (2021), Sánchez-Pi and Marti (2021), König et al. (2021), Budenny et al. (2022), Bolte et al. (2022), Georgiou et al. (2022), Wilson and Van der Velden (2022), primarily emphasize AI's environmental footprint (energetic efficiency, friendly scientific research, environmental sustainability of AI use, green software engineering research, governance, ethics, computational/energy efficiency, costs, green software engineering, and lifecycle sustainability) rather than its real application to face or solve citizens daily environmental problems.

On this basis, this study proposes the concept of ECO AI Initiatives. Building on the ISO (2024) understanding of AI as "computer systems capable of performing tasks that typically require human intelligence, such as reasoning, learning, perception, and language understanding," ECO AI Initiatives are defined as:

Integrated regulations (Acts/Laws/Mandates/Norms), strategic initiatives (Policies, Strategies, Roadmaps, Plans, Programs, Projects, Guidance) designed to address citizens' daily environmental challenges in urban cities through AI-enabled controlling, monitoring, prediction, regulating, reducing, decision-support, and automation solutions.

This concept is inspired by, but distinct from, broader frameworks such as the AI4SDGs Observatory (Vinuesa et al., 2020) and "Tackling Climate Change with Machine Learning" (Rolnick et al., 2023). ECO AI Initiatives explicitly: (i) integrate multiple governance layers with technical AI systems; (ii) focus on concrete, localized environmental issues experienced by citizens; and (iii) are tailored to the institutional and socio-environmental specificities of urban territories, such as Amazonian cities where hydrological, climatic, and socioeconomic vulnerabilities intersect.

Complementing, there are also ECO Non-AI Initiatives, traditional efforts to control, fund, monitor, prevent, predict, regulate, and reduce environmental problems, which create hybrid opportunities for AI use over time.

2.7. AI Techniques and Digital Enablers for Urban Water Management

The use of AI in water management has evolved progressively. Maier and Dandy (2000) provided an early review classifying ANN applications for water resources prediction. Joseph et al. (2022) introduced intelligent urban water networks integrating IoT, SCADA, and AI for leakage detection. Zhu et al. (2022) reviewed ML algorithms, including ANN, SVM, and LSTM, for water quality prediction. More recently, Moreno-Rodenas et al. (2025) advanced comprehensive AI techniques, including neural networks, GANs, and Explainable AI, for hydrology and ethical governance, while Kang et al. (2025) detailed sensor-IoT fusion with deep learning for real-time sewer monitoring.

A comprehensive bibliometric, literature, and document review identified 15 AI techniques (Appendix B; Figure 6) and 6 digital enablers (Appendix C: Big Data, Blockchain/Distributed Ledger Technology, Cloud Computing, Digital Twin, IoT/Sensing Infrastructure, and Open Data) applicable to urban water challenges. Far from exhaustive or complete, this analysis synthesizes the current state of the art in applying AI/machine learning and digital enablers, along with data-driven methodologies, to urban water systems, drawing on peer-reviewed literature from 2000 to 2026.

Appendix B is composed of fifteen AI techniques, short descriptions, applications, examples of authors (year), main authors (year), titles, resumes, and links related to 75 scientific articles or other official sources.

Appendix C catalogs information found from almost 50 articles, books, and other official sources. It consists of six digital enablers, a short description, applications, an example (author year), main author (year), title, summary, and a link. Digital enablers form an integrated ecosystem that enables AI deployment at scale. Together, they constitute a scalable infrastructure for evidence-based urban water governance.

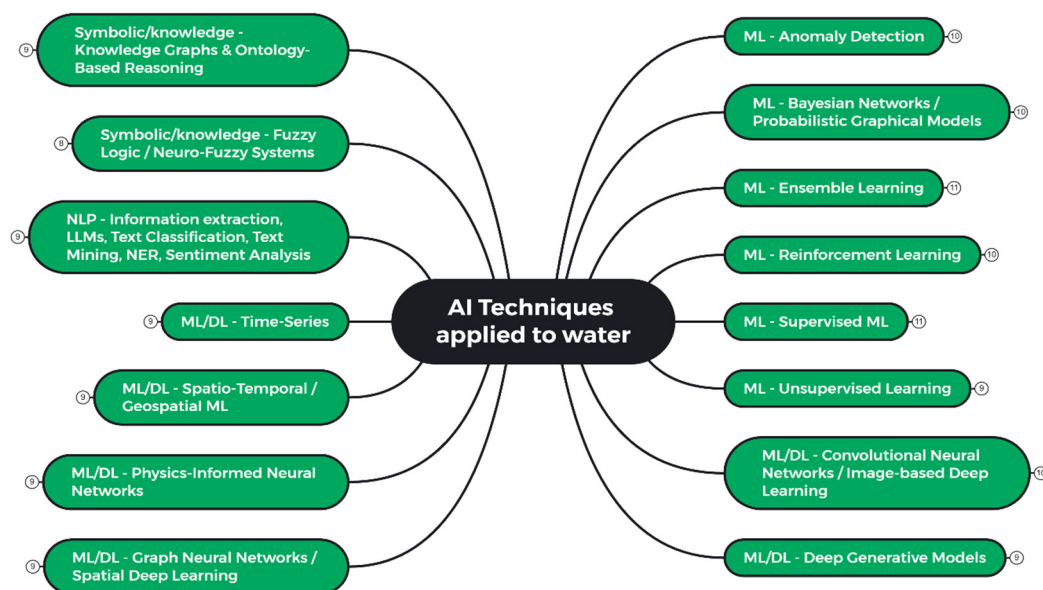


Figure 6. Main AI Techniques cited by multiple authors to address water issues.

3.3. Methodology

The study began in July 2025 and adopts an applied, mixed-methods approach structured into five phases, following open-science FAIR principles (Figure 7).

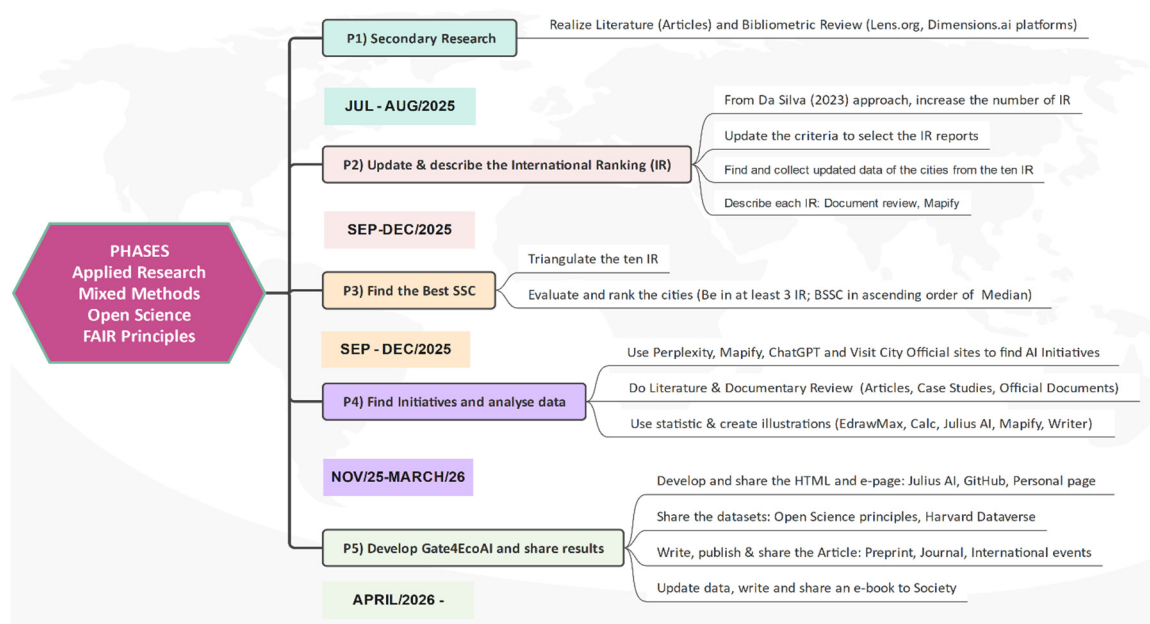


Figure 7. The five phases of Methodology.

3.1. Phase 1: Secondary Research (July–August 2025)

This phase used the open-source Lens.org platform, covering 307 million scholarly works, to conduct preliminary bibliometric reviews and identify supporting literature for the introduction and literature review sections. Lens.org was selected for its broad multidisciplinary coverage (307M scholarly works: peer-reviewed scientific articles, conference proceedings, books, etc.), advanced analytics, and strong support for open science and FAIR principles (Penfold, 2020; Spitschan et al., 2021; UNESCO, 2020; Wilkinson et al., 2016).

3.2. Phase 2: Updating the International Rankings (September–December 2025)

The number of international rankings was expanded from five (used in Da Silva, 2023) to ten, selected according to the following criteria: (1) published within the last five years; (2) related to Smart, Digital, or Sustainable Cities; (3) covering at least 20 cities from different continents; (4) freely accessible.

The ten rankings (Figure 5) were organized using the Mapify platform. Ranking data for 265 cities were consolidated into a single spreadsheet (Appendix D), including city profiles and positions in each ranking. City size follows UN (2025) categories: Very Small (50K–250K), Small (250K–1M), Medium (1M–5M), Large (5M–10M), and Mega (>10M). Capital Type is classified as National Capital, State Capital, Provincial Capital, or Non-Capital. Key derived indicators include: NTR (Number of Total Rankings, measuring cross-ranking visibility); MEAN and MEDIAN rank (measuring overall performance); SD (Standard Deviation, measuring consistency); and the composite BSSCs index (scaled 0–100). Cities are then classified into four tiers based on their BSSCs score.

3.3. Phase 3: Find and Classifying BSSCs (September–December 2025)

To accomplish this task, the process comprises 10 steps, including the creation of an indicator called **Benchmark Smart Sustainable Cities (BSSCs)**, as shown in Figure 8, and Appendix D1 explains each step of this phase.

Basically, this procedure combines JULIUS AI with descriptive statistics, percentile-based normalization, and weighted linear aggregation, and then conducts sensitivity analysis to finally rank and classify each city into four TIERS (GOLD, SILVER, BRONZE, and CRYSTAL).

The design follows standard practice in composite-indicator construction, using simple and transparent normative weights to encode the relative importance of dimensions, in line with the methodological recommendations of the OECD/European Commission–JRC Handbook on Constructing Composite Indicators (OECD/European Union/EC–JRC, 2008) and related European Union applications.

3.4. Phase 4: Identifying Initiatives and Analyzing Data (November 2025–March 2026)

This phase focused on initiatives found in the 20 Gold-tier BSSCs. A spreadsheet with 18 fields was created for data collection: City; Regulatory Initiatives (Acts, Laws, Standards, etc.); Strategic Initiatives (Roadmap, Plan, Project, Program, Strategy, Product, System, etc.); Main Environmental Area; Main Objective; Main Initiative Category; Initiative Type; Application to Water; Award Received; ECO Type; Possible AI Techniques; Possible Digital Enablers; Short Description; Main City Water Challenge; Period; Status (Jan 2026); Main Link; Second Link.

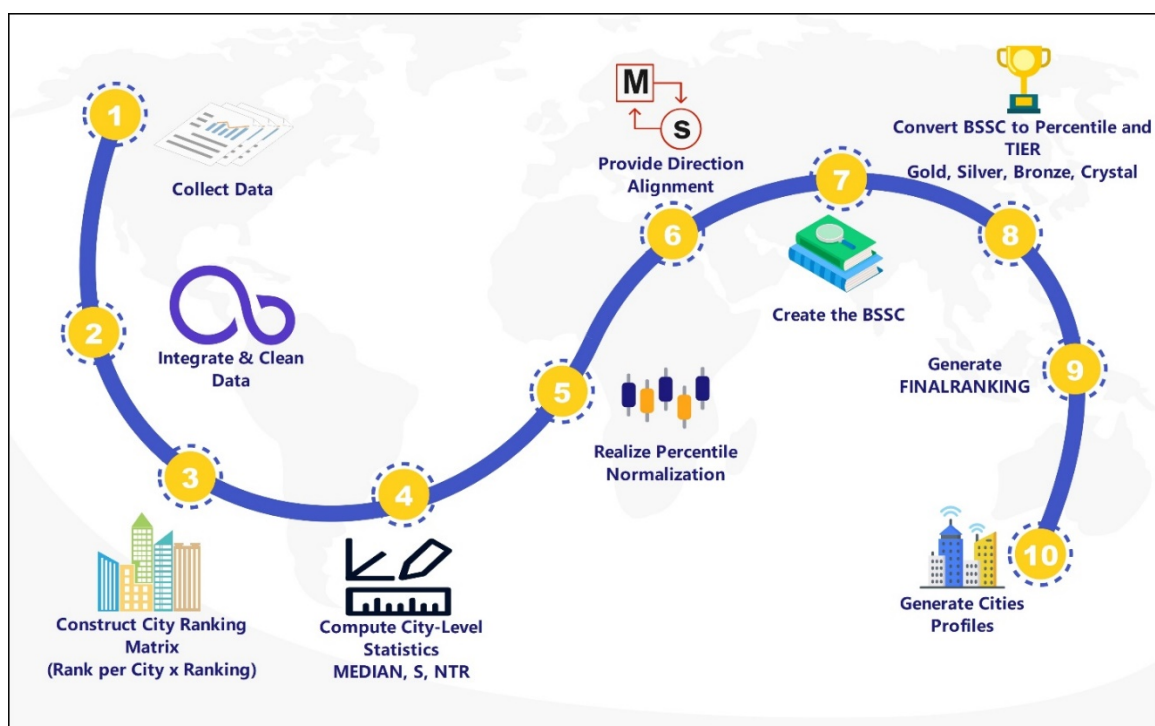


Figure 8. The process to identify and classify the BSSCs.

The Main Environmental Area comprises eight options (Afforestation, Air, Water, etc.) listed in Appendix F, most of which address environmental challenges in the city of Manaus. The Main Goal has ten alternatives (Control, Fund, Governance, Monitor, etc.) derived from the literature review, as shown in Appendix G, which contains the Main Goal, Selection Criteria, Keywords/Evidence, Examples, Author (Year), and Link.

The Main Initiative Category has nine options: Compliance & Regulation (AI), Compliance & Regulation (Non-AI), Digital Twin & Simulation, Network & Process Control, Predictive & Prevention, Quality Monitoring & Assessment, Resource Recovery & Reuse, Strategic Initiatives (AI), and Strategic Initiatives (Non-AI). Appendix H shows each Initiative Category, Examples, Author (Year), and Link, which were also built after the literature review.

The ECO Type field classifies initiatives such as: Eco AI (regulations/strategies involving AI); Eco Non-AI (traditional regulatory efforts without explicit AI); or Unclear (AI mentioned but not operationally confirmed).

The term “Possible AI Techniques” reflects a “best-evidence inference” made by the researcher from available sources (e.g., official city/utility documents, project pages, consortium reports, and

vendor documentation). In practice, a key difficulty was that many sources claimed to use “AI” or “smart” solutions but did not disclose specific techniques, likely for confidentiality, procurement, or communication reasons.

Therefore, entries in “Possible AI Techniques” and “Possible Digital Enablers” include only items that were “explicitly mentioned” or “clearly implied” by described system functions (such as sensor-driven monitoring, forecasting, or automated control). These fields should be seen as indicative, not as an audited inventory of implemented AI methods or Digital Enablers.

Appendix I shows the Description of four Status (Jan 2026): S1 - Pre-operational, S2 - Active – Early Implementation, S3 - Active – Fully Operational, S4 – Concluded.

To reduce time for searching data across multiple urban centers, Mapify AI and Perplexity AI were used initially, with several rounds of prompts listed in Appendix J. Mapify AI excels at transforming complex research queries into interactive mind maps with reports that visually cluster related sources, documents, and concepts, enabling rapid identification of key themes and connections across literature. Perplexity AI complements this by conducting real-time web searches using cited academic sources, synthesizing multi-perspective summaries from databases and portals, and generating downloadable tables or Excel files that streamline data aggregation and verification.

This combined data-driven AI approach aligns with open science principles advocated by researchers such as Thelwall (2025), who demonstrates Large Language Models (LLMs)' superiority over traditional bibliometrics for efficient research evaluation and literature synthesis through broader coverage and verifiable outputs, and Gundersen et al. (2025), whose replication studies show open data and code sharing dramatically improve AI research reproducibility from 33% to 86%, enabling scalable data collection and validation, and emphasizes the effectiveness of open science and the importance of adequately documenting data work.

However, since LLMs can suffer from hallucinations, outdated pre-training data, and limited attribution (Asai et al., 2026), it was necessary a second complementary documentary and literature review in the sources found, with additional search in academic databases (Lens.org), official public and companies sites, specialized platforms (AI4SDGs Think Tank, Climate Change AI, Global Water Awards, Legal500, Smart Water Magazine and iAgua Awards, Smart Cities World, Smart City portals), in order to refine the findings, yielding a structured dataset of initiatives organized in Appendix L for Phase 5.

3.5. Phase 5: Developing Gate4EcoAI and Disseminating Results (April 2026–)

The Appendix L dataset and four structured prompts (Appendices M–P) were used with Claude Sonnet 4.6 to generate HTML components (Appendices M1, N1, O1) and the interactive Gate4EcoAI platform, hosted on GitHub and accessible via the author's personal website (<https://www.jgsilva.org/projects>). Once the platform was developed, it was planned to deposit the article on Preprints.org (<https://www.preprints.org/>), submit to a peer-reviewed journal, and, if possible, present the results at international conferences or publish an e-book.

This phase adheres to Open Science and FAIR data principles (Hosseini et al., 2024; UNESCO, 2020; Wilkinson et al., 2016) by ensuring that all data are openly and persistently accessible.

4. Main Results and Discussion

4.1. Robustness of the BSSC Selection from the Ten International Rankings

The ten international rankings together provide comprehensive coverage, with 528 verified indicators evaluating 265 cities from 98 countries across six continents (latest editions, 2021–2025). Despite their heterogeneity across governance, digitalization, sustainability, economy, tourism, livability, and urban performance metrics, the rankings show substantial statistical concordance, as shown in Table 3.

Table 3. Spearman Rank Correlations across all rankings.

INTERNATIONAL RANKINGS	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
R1: 50 SC Gov. 2021	1.00	-0.17	0.22	0.48	-0.13	0.03	0.15	0.14	0.21	0.35
R2: 31 SC Index Rep 2022	-0.17	1.00	0.23	-0.31	-0.09	0.12	-0.02	-0.04	-0.02	-0.23
R3: 30 DC Index 2022	0.22	0.23	1.00	0.55	0.25	0.81	0.81	0.72	0.09	0.64
R4: 20 Global SC 2022	0.48	-0.31	0.55	1.00	0.26	0.54	0.69	0.58	0.50	0.73
R5: 70 The Corporate Knights SustCities Index 2023	-0.13	-0.09	0.25	0.26	1.00	0.71	0.73	0.49	0.04	0.39
R6: 100 The Arcadis SustCities Index 2024	0.03	0.12	0.81	0.54	0.71	1.00	0.76	0.76	0.04	0.80
R7: 183 Cities in Motion Index 2025	0.15	-0.02	0.81	0.69	0.73	0.76	1.00	0.68	0.19	0.82
R8: 146 IMD SC Index 2025	0.14	-0.04	0.72	0.58	0.49	0.76	0.68	1.00	0.08	0.57
R9: 40 GDS Index Report 2025	0.21	-0.02	0.09	0.50	0.04	0.04	0.19	0.08	1.00	-0.05
R10: 48 Global Power City Index (GPCI) 2025	0.35	-0.23	0.64	0.73	0.39	0.80	0.82	0.57	-0.05	1.00

The pairwise Spearman rank correlation across all rankings of Appendix D, revealed that:

There is a very strong (green) positive association among multidimensional indices: Cities in Motion Index (R7), Arcadis SCI (R6), Corporate Knights SCI (R5), Digital Cities Index (R3), GPCI (R10), IMD SCI (R8), and the Global Smart Cities ranking (R4) show moderate positive correlations.

This means cities that rank well in one of these tend to rank well in the others. For example, the Digital Cities Index (R3) is very strongly associated with the Arcadis Sustainable Cities Index (R6, $\rho \approx 0.81$) and the Cities in Motion Index (R7, $\rho \approx 0.81$), and strongly associated with the IMD SC Index 2025 (R8, $\rho \approx 0.72$) and Global Power City Index (R10, $\rho \approx 0.64$). Similarly, the Global Smart City ranking (R4) correlates positively, in a moderate-to-strong manner, with R3 ($\rho \approx 0.55$), R6 ($\rho \approx 0.54$), R7 ($\rho \approx 0.69$), R8 ($\rho \approx 0.58$), and R10 ($\rho \approx 0.73$).

The sustainability-focused indices are also mutually reinforcing: Corporate Knights (R5) is strongly correlated with Arcadis (R6, $\rho \approx 0.71$) and Cities in Motion (R7, $\rho \approx 0.73$), indicating that cities that are sustainable in one framework tend to be well rated in others.

At the same time, the correlations are not perfect, and a few pairs even show weak or negative associations, which signals that the rankings bring complementary perspectives rather than simply duplicating each other. The ranking focusing on Smart governance or tourism sustainability (R1 Top 50 Smart Governments, R2 Smart Cities Index Report, and R9 GDS) shows a weaker correlation with the others and sometimes even weakly negative with a few indices. That may reflect their more specialized focus rather than a broad, general-purpose measure of city performance.

Overall, this pattern, strong positive correlations among the main composite indices, and weaker or mixed correlations for more specialized rankings, indicates that the ten rankings share a robust common signal about city performance while still adding diverse information, justifying their joint use to construct stable and informative BSSCs.

4.2. Relationship of the Ten Rankings with Sustainability

Six of the ten rankings measure sustainability directly (R2: Smart Cities Index Report; R3: Digital Cities Index; R5: Corporate Knights SCI; R6: Arcadis SCI; R7: Cities in Motion; R9: GDS Index; R10: Global Power City Index), with dedicated sections for environmental performance and resource efficiency. The remaining three (R1: Top 50 Smart City Governments; R4: Global Smart Cities; R8: IMD SCI) weave sustainability into governance quality, infrastructure, and overall quality of life.

Despite these different approaches, cities such as London, Oslo, and Copenhagen consistently rise to the top, indicating a broad consensus that they lead in combining digital innovation with environmental and social progress.

4.3. Profile of the 99 Selected BSSCs

4.3.1. City Size and Capital Type

Among the 99 BSSCs, medium-sized cities (43; 1M–5M inhabitants) are most common, followed by megacities (26; >10M), small cities (16; 250K–1M), large cities (13; 5M–10M), and one very small city. This pattern reflects a balance between global "heavyweight" urban centers and medium-sized cities that lead in innovation, sustainability, and governance, rather than focusing exclusively on

megacities. Table 4 confirms that medium and mega cities are consistently the most represented, especially in broad, high-coverage indices like R6, R7, and R8.

Table 4. Number and Percentage of Cities by Ranking and City Size.

City Size	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Large	6	6	7	4	8	13	12	12	3	9
Medium	20	16	10	6	18	35	41	41	14	17
Mega	6	7	11	10	17	24	26	23	0	15
Small	3	1	2	0	6	11	16	15	3	6
Very Small	0	0	0	0	0	0	1	1	1	0
TOTAL	35	30	30	20	49	83	96	92	21	47
City Size	R1 (%)	R2 (%)	R3 (%)	R4 (%)	R5 (%)	R6 (%)	R7 (%)	R8 (%)	R9 (%)	R10 (%)
Large	17,14	20,00	23,33	20,00	16,33	15,66	12,50	13,04	14,29	19,15
Medium	57,14	53,33	33,33	17,14	36,73	42,17	42,71	44,57	66,67	36,17
Mega	17,14	23,33	36,67	28,57	34,69	28,92	27,08	25,00	0,00	31,91
Small	8,57	3,33	6,67	0,00	12,24	13,25	16,67	16,30	14,29	12,77
Very Small	0,00	0,00	0,00	0,00	0,00	0,00	1,04	1,09	4,76	0,00
TOTAL	100	100	100	65,7143	100	100	100	100	100	100

In political-administrative terms (Table 5), national capitals dominate (45 cities; appearing in at least 40% of each ranking). Non-capital cities (20) and sub-national capitals (state: 13; provincial: 7) are present in every major ranking, particularly those with more extensive coverage.

This structural bias toward national capitals likely reflects their greater data availability, institutional capacity, and prominence as national urban hubs.

Table 5. Number of Cities in each Ranking by Capital Type.

Capital Type	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Autonomous Community Capital	1	1	1	0	0	1	1	1	1	1
Canton Capital	1	0	1	0	0	2	2	2	0	2
Department Capital	0	0	0	0	1	0	1	1	0	0
Legislative Capital	0	0	0	0	1	1	1	1	0	0
Metropolitan Capital	1	1	0	0	0	0	0	1	0	0
National Capital	17	17	19	10	20	37	45	44	9	24
Non-Capital	8	6	3	4	13	19	20	16	3	7
Prefecture Capital	0	1	0	0	0	0	1	1	0	1
Provincial Capital	1	0	1	1	5	6	6	5	1	3
Region Capital	1	0	1	0	1	3	5	5	4	1
Special Administrative Region	0	0	1	1	1	1	1	1	0	1
State Capital	4	3	3	4	6	12	12	13	3	6
Territorial Capital	1	1	0	0	1	1	1	1	0	1
TOTAL	35	30	30	20	49	83	96	92	21	47

4.3.2. Continent and Country

The 99 BSSCs are strongly concentrated in Europe (40 cities; 40%), followed by Asia (23; 23%) and North America (17; 17%), with smaller representation from South America (7; 7%), Africa (6; 6%), and Oceania (6; 6%). The USA (12 cities), China (7), UK (5), Germany (4), and Canada (4) together account for 32 of the 99 cities. This geographic concentration confirms findings from prior reviews (Anthopoulos, 2017; Robin and Acuto, 2018; Burns et al., 2021; Da Silva, 2023 p. 24) that both practice and research are dominated by affluent cities in the Global North.

In addition, more recently, an ambitious initiative to develop around 120 Climate-Neutral and Smart Cities by 2030 under the EU Mission framework, is likely to amplify this advantage: it concentrates substantial resources, such as around €120 million in annual funding from Horizon Europe (European Commission, 2024), experimentation capacity and knowledge exchange in a large

cohort of European cities, reinforcing their global visibility as “front-runner” smart and sustainable urban laboratories.

Critically, this result also exposes a structural asymmetry: few other regions have comparable multi-level governance, binding climate legislation, and sustained mission-oriented funding for cities, so places like Latin America and Brazil, which face intense socio-environmental pressures but operate with more fragmented and volatile policy and funding environments, risk falling further behind in international smart and sustainable city benchmarks despite arguably greater needs.

4.4 TIER Distribution and the Focus on Gold BSSCs

As shown in Appendix E, the 99 cities are distributed across four tiers, and Figure 9 shows the distribution of BSSCs' score by city type, based on population size (2025).

The Gold tier comprises 20 cities: London (1st), Seoul (2nd), Copenhagen (3rd), Berlin (4th), Singapore (5th), Amsterdam (6th), Sydney (7th), New York (8th), Oslo (9th), Beijing (10th), Helsinki (11th), Stockholm (12th), Shanghai (13th), Vienna (14th), Madrid (15th), Melbourne (16th), Dubai (17th), Hong Kong (18th), Paris (19th), and Zurich (20th). Gold cities display BSSC scores with a mean of approximately 90.47, a median of 89.81, and a standard deviation of 3.76.

The Silver tier (20 cities) has a mean of approximately 79.21, median 79.99, SD 3.36. The Bronze tier (20 cities) shows a mean of approximately 67.65, median 66.59, SD 3.57. The Crystal tier (39 cities) has a mean of approximately 51.42, median 53.25, SD 8.26, reflecting both lower scores and greater dispersion (Table 6).

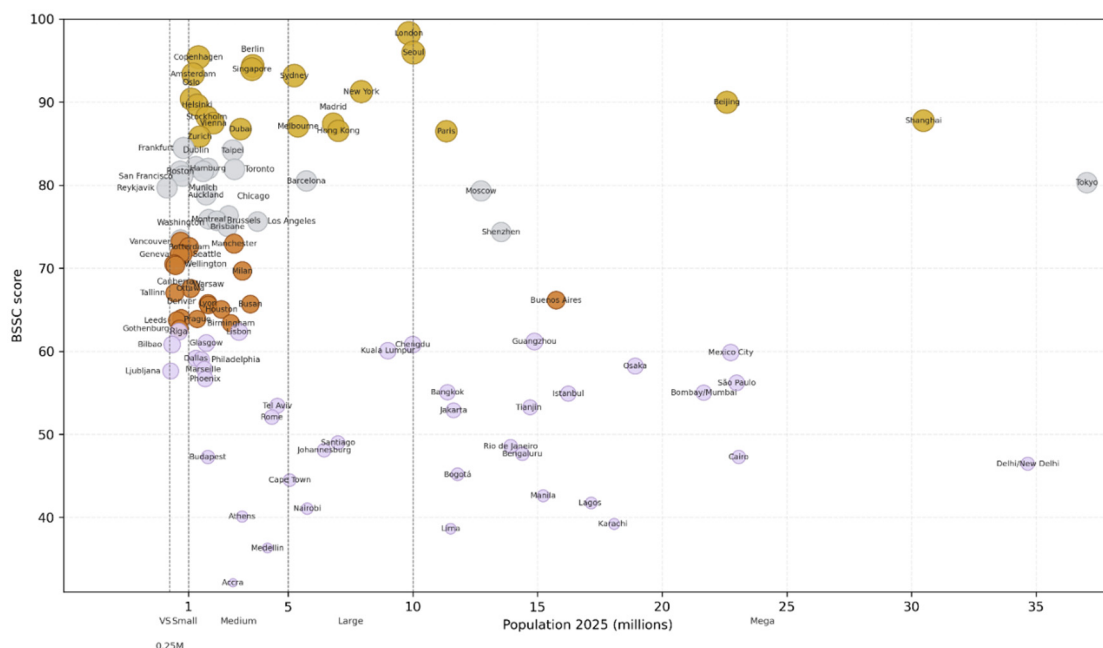


Figure 9. Distribution of 99 BSSCs by Tier versus City Type.

Table 6. Statistics of Cities by Tier and Size.

Tier	VS	Small	Medium	Large	Mega	N	X1 BSSC	X2 BSSC	MED1 BSSC	MED2 BSSC
Gold	0 (0%)	0 (0%)	10 (50%)	6 (30%)	4 (20%)	20	90.46	90.46	89.81	89.81
Silver	1 (5%)	4 (20%)	11 (55%)	1 (5%)	3 (15%)	20	79.21		79.99	
Bronze	0 (0%)	9 (45%)	10 (50%)	0 (0%)	1 (5%)	20	67.65	62.56	66.59	62.71
Crystal	0 (0%)	3 (7.7%)	12 (30.8%)	6 (15.4%)	18 (46.2%)	39	51.42		53.25	
TOTAL	1	16	43	13	26	99	68.19	68.19	67.02	67.02

Most Gold-tier cities (80%) are medium- and large-sized and display markedly higher BSSC values (mean ≈ 90.5 ; median ≈ 89.8) than the combined non-Gold tiers (overall mean ≈ 62.6 ; median ≈ 62.7). Welch's two-sample t-test, specifically recommended for continuous index data when group variances and sample sizes are unequal (Welch, 1947; Ruxton, 2006; Delacre et al., 2017), confirms that Gold cities are statistically distinct from all non-Gold cities: the average BSSCs difference is approximately 27.9, $t(\approx 96) = 16.2$, $p < 0.001$, with a very large effect size (Cohen's $d \approx 2.3$; Cohen, 1988). In practical terms, this means that Gold cities are not just slightly better but clearly separated from the rest of the distribution, which justifies focusing the subsequent analysis on Gold-tier cities as a distinct benchmark group for high BSSC performance.

4.5. Profile of Gold BSSCs: Initiative Types

The Appendix L dataset contains 333 entries across 20 Gold cities and 11 EU-level initiatives. Most (249; 75%) are Strategic Initiatives, while 84 (25%) are Regulatory Initiatives.

Across the 84 Regulatory Initiatives, the largest category is national water legislation (24; 28.6%; Dutch Water Management Act, Danish Water Planning Act, etc.), followed by national environmental legislation (12; 14.3%; Chinese Environmental Protection Law, UK Environment Act 2021, etc.) and national technical standards (8; 9.5%, primarily from China). AI-specific regulatory instruments remain marginal: national AI legislation (2.4%; USA National AI Initiative Act of 2020 and South Korea AI Basic Act), national AI guidance (1.2%; Danish Regulatory Sandbox for AI), and national AI agency (1.2%; Spain's AESIA). The regulatory portfolio is therefore dominated by traditional water and environmental legal frameworks, with AI-native governance instruments appearing only at the margins.

Among the 249 Strategic Initiatives, the most common type is national AI framework/plan/program/strategy (21; 8.4%; Australia's National AI Plan, Germany AI Strategy, UK National AI Strategy, etc.), followed by supranational demonstration projects led by the EU (13; 5.2%) and national water utility/company-led platforms by Singapore PUB (13; 5.2%). The largest municipal cluster is stormwater management/project/strategy/system (10; 4.0%; Copenhagen's Cloudburst Management Plan, NYC's Stormwater Resiliency Plan, etc.).

4.6. Profile of Gold BSSCs: Cities, Environmental Areas, Goals, and Categories

Figure 10 shows that Singapore leads with 37 initiatives, followed by Sydney (28), NY City (22), London (21), Melbourne (18), and Beijing (18), while Zurich (9), Hong Kong (10), and Helsinki (10) have the lowest number of initiatives. It is important to note that while Singapore and Sydney have the largest strategic portfolios, the regulatory activity is more concentrated in a few places, such as Shanghai and Beijing.

In the Main Environmental Area, 224 initiatives (67.3%) are directly related to Water, making it by far the most frequent environmental focus in Appendix L. The remaining initiatives are split between Not environmental/Other (52, 15.6%), such as AI initiatives (South Korea AI Basic Act, Singapore Lorong AI, etc.), and Multi-Environmental Area (50 initiatives, 15.0%), which includes initiatives spanning multiple domains (often including water) and therefore reflects more integrated or cross-sector framing rather than a single-environment focus. Solid Waste/Garbage is comparatively rare (7 initiatives, 2.1%), suggesting that waste-focused actions, including those with potential *indirect* implications for water outcomes, are much less frequently documented than initiatives coded as directly water-related within this appendix.

Concerning the Main Goal, Governance is the most common goal with 90 initiatives (27.0%), followed closely by Regulate with 84 (25.2%). Together, these two account for just over half of all entries (52.3%), indicating that the appendix emphasizes institutional arrangements, planning, coordination, and rule-setting as the dominant framing of initiatives.

A second tier of objectives focuses on information and performance: Monitor represents 56 initiatives (16.8%), and Reduce represents 40 (12.0%), suggesting substantial attention to measurement and surveillance, as well as outcome-oriented reduction efforts. The remaining goals

are comparatively less frequent: Predict 18 (5.4%), Fund 14 (4.2%), Optimize 14 (4.2%), Prevent 11 (3.3%), and Control 6 (1.8%), imply that forecasting, resource allocation, and operational control functions are present but less prominently represented than governance and regulatory approaches.

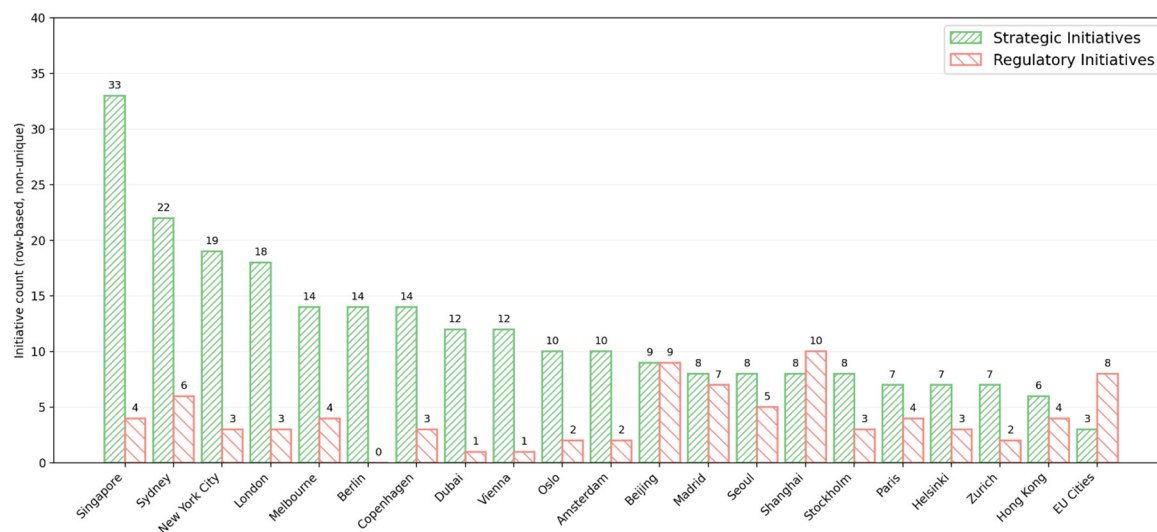


Figure 10. Regulatory and Strategic Initiatives per city.

When the analysis focuses only on 224 initiatives (67.3%) directly related to Water (Figure 11), the most common Main Goal is Monitor with 53 initiatives (23.7%), followed by Regulate with 47 (21.0%). Together, monitoring and regulation account for 44.7% of all water-related entries, indicating that water initiatives in this appendix are most often framed around measurement/surveillance and rule-setting/compliance.

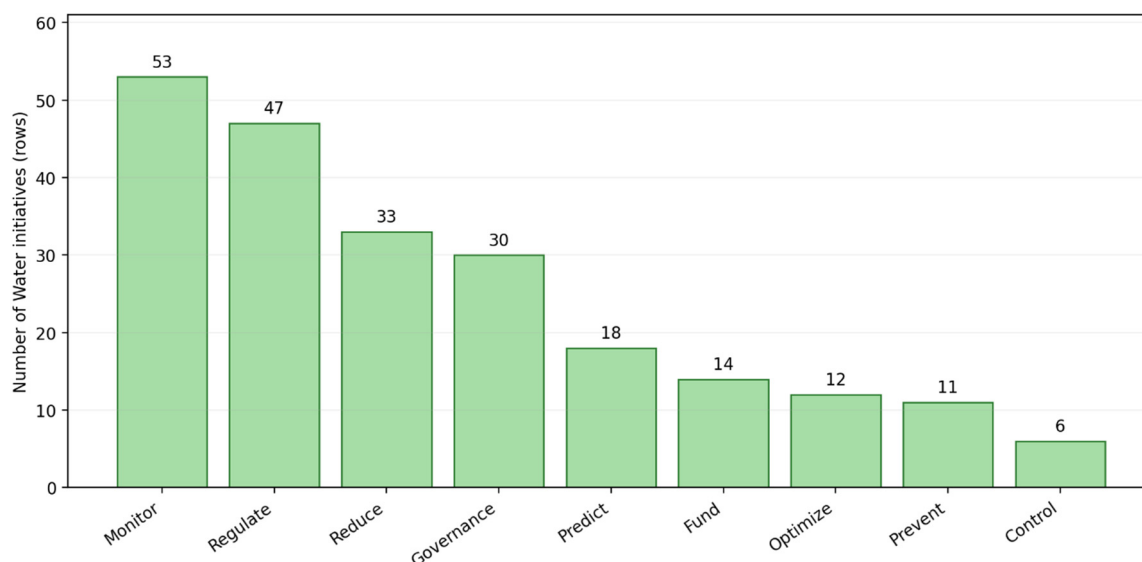


Figure 11. Main Goal distribution for initiatives directly related to Water (n = 224).

A second tier of goals includes Reduce with 33 (14.7%) and Governance with 30 (13.4%), suggesting substantial emphasis on both outcome-oriented reduction (e.g., lowering pollution, leakage, risk) and coordination/management structures. The remaining goals are less prevalent but still meaningful: Predict 18 (8.0%), Fund 14 (6.2%), Optimize 12 (5.4%), Prevent 11 (4.9%), and Control 6 (2.7%), implying that forecasting and optimization appear, but are not the dominant framing for water initiatives in this dataset.

Across the full Appendix L, the Main Initiative Category distribution is led by Compliance & Regulation (Non-AI) with 76 initiatives (22.8%), followed by Strategic Initiatives (AI) with 49 (14.7%) and Network & Process Control with 48 (14.4%). A large middle share is also captured by Quality Monitoring & Assessment 45 (13.5%) and Predictive & Prevention 42 (12.6%), indicating that beyond compliance, a substantial portion of initiatives focus on operational control, monitoring, and forward-looking risk reduction. Categories tied to advanced modeling are present but smaller in volume, such as Digital Twin & Simulation 17 (5.1%), while Compliance & Regulation (AI) is comparatively rare at 9 (2.7%).

However, restricting to the 224 Water initiatives, the distribution shifts toward more operational categories. The two most frequent categories are tied at the top: Compliance & Regulation (Non-AI) (48; 21.4%) and Network & Process Control 48 (48; 21.4%). Next come Quality Monitoring & Assessment (41; 18.3%) and Predictive & Prevention (39; 17.4%). Together, these four categories account for 78.5% of all water-related initiatives, suggesting that entries in this appendix are primarily framed around compliance, system control, monitoring, and prevention. Strategic categories appear less prominent in water, specifically for Strategic Initiatives (Non-AI) (18; 8.0%) and Strategic Initiatives (AI) (9; 4.0%).

It is important to note that the descriptive results reported above are based on row-level entries, and some initiatives appear multiple times because they are shared across multiple cities (particularly national-scale regulatory or strategic programs).

To assess whether this duplication biases the findings, the same calculations were repeated using unique initiatives by removing duplicate initiative names. This adjustment reduces the sample from 333 records to 318 unique initiatives, but it does not materially change the distributions underlying the analysis. Formal chi-square tests comparing row-based versus unique-initiative distributions show no statistically significant differences for Main Environmental Area ($p = 0.969$), Main Goal ($p = 0.99997$), or Main Initiative Category ($p = 0.99996$), with negligible effect sizes (Cramér's $V \approx 0.02$ in all cases).

In practical terms, the headline patterns are robust to whether initiatives are counted as repeated city entries or as unique cases.

4.7. Possible AI Techniques and Possible Digital Enablers in Gold BSSCs

A structurally significant element emerges from the regulatory portfolio. Across all 84 Regulatory Initiatives, no AI Technique is mentioned. Digital Enablers appears only once, in the USA National Artificial Intelligence Initiative Act of 2020, which mentions Open Data (U.S. House, 2020). All 233 AI-technique attributions and nearly all 254 digital-enabler mentions come exclusively from Strategic Initiatives.

This regulatory silence, amid a dominance of strategy, signals a policy gap: enforceable laws lag behind visionary modernization and recommendations for smart water management technologies, risking uneven AI adoption to address urban water challenges such as aging infrastructure, operational inefficiencies, pollution, and other issues described in Appendix L.

To bridge it, regulatory bodies or policy makers should craft clear guidelines addressing data security, privacy, standardization, transparency, explainability, and ethical AI and Digital Enablers use, fostering national-international collaboration for harmonized innovation while upholding standards, addressing institutional barriers via expertise/regulatory updates, as recommended by Asgari and Nematy (2022), Moreno-Rodenas et al. (2025), and concluded by Dada et al. (2024): "Regulatory and policy frameworks play a pivotal role in shaping the trajectory of smart water management... collaborative efforts... become imperative for ensuring a harmonized approach that fosters innovation while upholding ethical standards".

Among the 249 Strategic Initiatives, 87 (36%) include at least one attributed AI technique. Of the 15 techniques identified in Appendix B, only 10 appear in practice (Figure 12). ML–Anomaly Detection and ML–Supervised ML jointly dominate (46 mentions each), reflecting cities' preference

for proven, reliability-oriented deployment paths with measurable ROI in monitoring, early warning, and infrastructure inspection. CNN/Image-based Deep Learning (27) remains substantial.

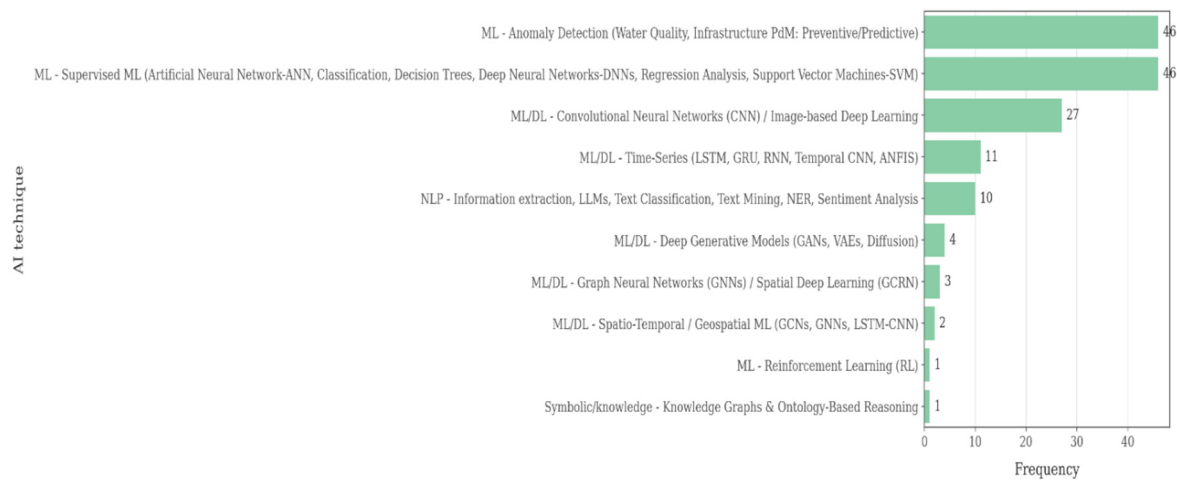


Figure 12. Distribution of AI Techniques potentially used by 87 Strategic Initiatives.

By contrast, other AI Techniques appear far less often in the Strategic Initiative sources content such as ML/DL - Time-Series (11), NLP/LLM-related techniques (10), ML/DL - Deep Generative Models (4), ML/DL - Graph Neural Networks (GNNs) / Spatial Deep Learning (GCRN) (3), and only isolated mentions of ML/DL - Spatio-Temporal / Geospatial ML (GCNs, GNNs, LSTM-CNN) (2), ML - Reinforcement Learning (1), and Symbolic/knowledge - Knowledge Graphs & Ontology-Based Reasoning (1), which may suggest that Appendix L's AI footprint is currently anchored in mature monitoring and prediction paradigms.

Five AI techniques (Bayesian Networks, Ensemble Learning, Unsupervised Learning, Physics-Informed Neural Networks, and Fuzzy Logic) are entirely absent from identified city practices despite scientific support, which may expose a science-to-practice gap.

In terms of digital enablers, 142 strategic initiative rows include at least one enabler. IoT and sensing infrastructure dominates (101 mentions), confirming its role as the universal prerequisite for smart water management. Cloud computing (62) and Big Data (37) follow as the analytics backbone; Digital Twins (25) and Open Data (24) characterize more mature programs; On the other hand, Blockchain (1) is essentially absent, implying it's not a mainstream enabling layer for these initiatives in the way sensing and cloud are. Finally, eight Strategic Initiatives were identified that use more than three digital enablers and are referred to as multi-digital enablers.

4.8. ECO AI and ECO Non-AI Initiatives in Gold BSSCs

Among the 333 initiatives, the majority (174; 52.25%) are classified as Eco Non-AI, while Eco AI accounts for 128 (38.44%), and 31 (9.31%) are Unclear. Analyzing ECO Type by Main Goal (Figure 13), Eco AI clusters around operational intelligence goals: Monitor (28.1%) and Governance (23.4%), with meaningful shares in Predict (10.2%) and Optimize (7.0%), indicating that AI is primarily deployed for sensing, interpretation, and operational steering.

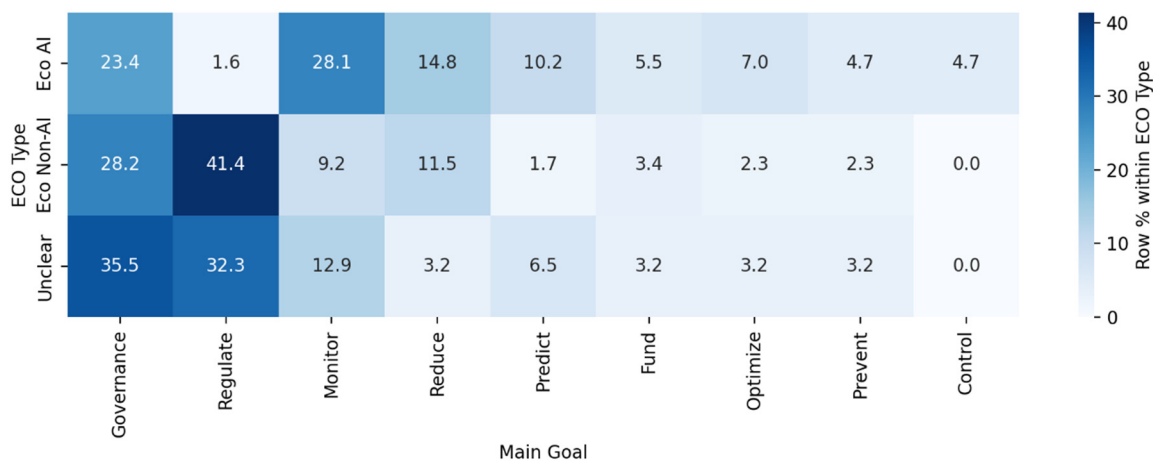


Figure 13. ECO Type (%) by Main Goal heatmap.

Eco Non-AI shows the opposite profile, dominated by Regulate (41.4%) and Governance (28.2%), with Predict nearly absent (1.7%). For policymakers, this is a clear division of labor: regulation is still being delivered mostly through conventional instruments, while AI is being deployed where continuous measurement and adaptive control are needed.

Unclear looks like a governance-and-regulation bucket too (Governance 35.5%, Regulate 32.3%), which suggests many “Unclear” entries are not ambiguous because they are borderline AI, but because they’re institutional initiatives whose components aren’t described consistently.

When that analysis focuses on Main Initiative Categories (Figure 14), Eco AI concentrates on delivery-oriented, operations-heavy categories: It is dominated by Predictive & Prevention (25.0%), Strategic Initiatives (AI) (26.6%), and Network & Process Control (21.9%). That combination is a strong signal that when initiatives are tagged Eco AI, they’re typically framed as performance and reliability interventions, not just generic digital upgrades.

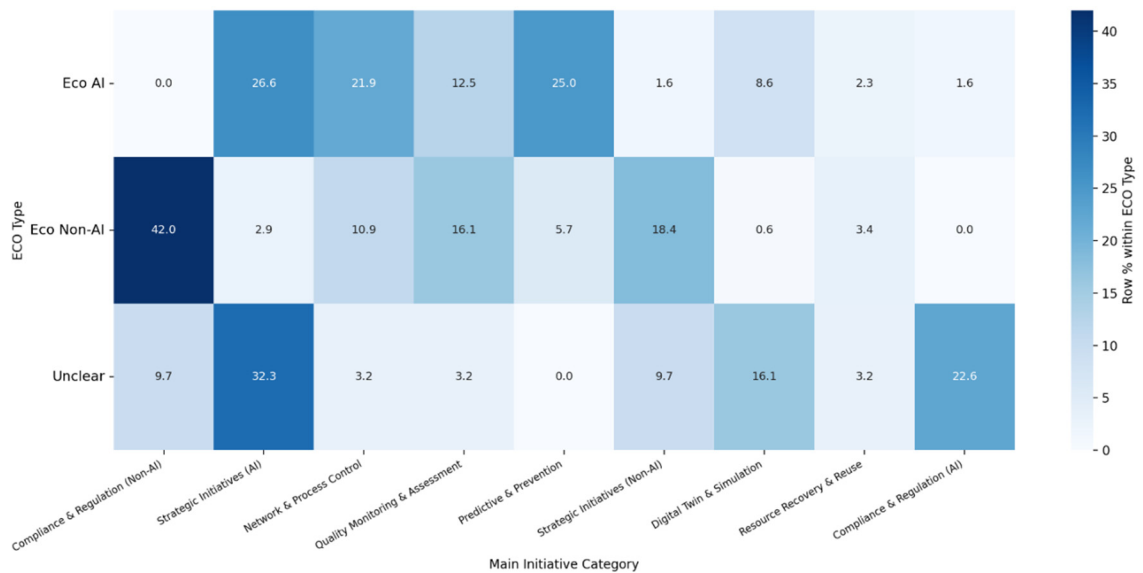


Figure 14. ECO Type (%) by Main Initiative Category heatmap.

Eco Non-AI is structurally different and much more compliance-led. Compliance & Regulation (Non-AI) alone accounts for 42.0% of Eco Non-AI, with another large block in Strategic Initiatives (Non-AI) (18.4%) and Quality Monitoring & Assessment (16.1%). For policymakers, the striking implication is that the “non-AI” portfolio is where rule-setting and compliance programs reside,

while the “AI” portfolio is where operational control and prevention programs reside, two policy levers that often sit in different departments and funding lines.

Unclear is the most revealing row from a governance standpoint. It has unusually high shares in Strategic Initiatives (AI) (32.3%) and Compliance & Regulation (AI) (22.6%) plus Digital Twin & Simulation (16.1%), which suggests the ambiguity isn't random, it clusters in categories where labels are easy to overuse and hard to verify. A practical takeaway is that improving disclosure requirements (what model, what data, what decision it supports) specifically for AI compliance and digital twin initiatives would likely shrink the Unclear bucket quickly and make the portfolio easier to audit and compare across jurisdictions.

To give some examples, using a simple combined-strength score (distinct AI-technique tags plus distinct digital-enabler tags listed per initiative), some strong ECO AI initiatives stand out because they seem to use both the algorithms and the infrastructure needed to run them in practice:

Case 1) London's Microsoft Project (FIDO Aqual Plus – AI Leak Detection System), a Lighthouse Award 2024 winner, is the strongest example, pairing ML anomaly detection, supervised ML, and NLP with big data, cloud, and IoT/sensing foundations (FIDO, 2025).

Case 2) Dubai's DEWA Hydro Insight Smart Meter Analytics System, awarded Smart Water Project of the Year 2024 at the Global Water Awards, shows a similarly “full-stack” profile. It supports monitoring of over 1 million smart meters and reportedly reduced meter anomaly detection time from 30 days to 1 hour, conserving 214 million gallons of water (DEWA, 2024).

Other high-scoring initiatives that feed directly into the Gate4EcoAI platform include Sydney's NSW Flood and Storm Intelligence Sensing, Seoul's Smart Flood Alert System, and Singapore's Changi Water Reclamation Plant and JACOBS Replica™ Digital Twin.

4.9. The Gate4EcoAI Platform

The Gate4EcoAI is more than a repository (Figure 15), it is a digital platform that serves as an evidence-to-policy bridge.



Figure 15. Interface of the Gate4EcoAI Digital Platform.

It translates 333 classified initiatives from 20 world-leading cities into an interactive, filterable, and exportable knowledge system. It links initiative types, AI techniques, digital enablers, and

operational statuses in a single interface. No comparable open-access tool exists calibrated to the environmental priorities of a Global South city.

It begins with urban water management, Manaus's primary challenge, but is designed to expand progressively to solid waste, air pollution, urban afforestation, traffic congestion, and energy management. Each expansion will follow the same evidence-based, FAIR-compliant methodology established here. Basically, its button navigation structure features nine main entry points:

B1) The Researcher Page links to the investigator's home page; B2) The Authors of AI Techniques and B3) Authors of Digital Enablers pages display technique/enabler information with access to source documents; B4) The Dashboard provides data visualization with indicators organized in six sections; B5) Regulatory Initiatives and B6) Strategic Initiatives buttons generate dynamically filtered DataTables; B7) The Customize and Print button allows users to select up to 7 variables from the 18-field taxonomic schema to generate an exportable and printable PDF report; B8) The Clear function resets the interface to its default state; B9) The Evaluate the Platform button directs users to a 7-question digital feedback questionnaire.

5. Conclusions

The study addressed five research questions, yielding the following conclusions, limitations, and recommendations for future research:

C1) London, Seoul, Copenhagen, Berlin, Singapore, Amsterdam, Sydney, New York, Oslo, Beijing, Helsinki, Stockholm, Shanghai, Vienna, Madrid, Melbourne, Dubai, Hong Kong, Paris, and Zurich are the world's leading Smart Sustainable Cities, statistically distinct from all other tiers, predominantly medium-sized national capitals concentrated in Europe (40%) and Asia (23%). Singapore leads in total initiatives, followed by Sydney, New York City, and London; regulatory activity is most concentrated in Shanghai and Beijing.

Water utility managers and policymakers in Manaus and other cities should consider benchmarking visits to these leading cities, and researchers should investigate the most effective water management practices, particularly how they engage citizens, companies, universities in preventing and reducing **water pollution**, a challenge that was not deeply examined in this study.

Future research should also examine what governance reforms and funding mechanisms could enable cities like Manaus to build the institutional foundations necessary for smart, sustainable city initiatives, closing the structural gap that currently separates them from Gold BSSCs. On the NTR ≥ 3 threshold: future research could explore an NTR ≥ 2 threshold to determine whether cities from underrepresented regions, particularly South America and Africa, would qualify as national or regional leaders.

C2) The research found 333 initiatives, 249 (75%) Strategic and 84 (25%) Regulatory, across 20 Gold cities and the EU, of which 174 (52.25%) are Eco Non-AI, 128 (38.44%) Eco AI, and 31 (9.31%) Unclear, revealing an institutional division of labor: conventional regulatory instruments govern rule-setting and compliance, while AI is concentrated in operational delivery. Critically, the 84 Regulatory Initiatives make no mention of AI techniques and reference digital enablers only once, signaling a policy gap. To bridge it, regulatory bodies or policymakers should craft clear guidelines addressing data security, privacy, standardization, transparency, explainability, and ethical use of AI and Digital Enablers, fostering national-international collaboration for harmonized innovation while upholding standards and addressing institutional barriers through expertise/regulatory updates.

A key limitation is that ECO Type classification relies on publicly available documentation, and the 9.31% Unclear entries, clustering in AI compliance and digital twin categories, reflect widespread AI overclaiming without operational confirmation about the techniques used, which may distort the true Eco AI share. Future research should develop standardized AI disclosure requirements in public procurement and reporting, expand the dataset to Silver and Bronze BSSCs cities to identify more accessible and cost-proportionate models for cities like Manaus, and conduct longitudinal tracking of initiative outcomes to move beyond classification toward verified environmental impact.

C3) Of 15 AI techniques identified in the literature, only 10 appear in city practice. ML–Anomaly Detection and ML–Supervised ML dominate, with 46 mentions each. CNN/Image-based Deep Learning follows with 27 mentions. Five techniques are entirely absent from identified practice: Bayesian Networks, Ensemble Learning, Unsupervised Learning, Physics-Informed Neural Networks, and Fuzzy Logic. All five have peer-reviewed support for water management applications, as documented in Appendix B.

Two interpretations are plausible. First, the absence may reflect a genuine technology transfer gap, validated techniques developed in research settings have not been adopted at scale in city operations. Second, it may reflect a disclosure gap, many utilities and vendors withhold specific algorithmic details for confidentiality or procurement reasons. Under this interpretation, the dominance of Anomaly Detection and Supervised ML reflects what cities communicate publicly, not necessarily what they deploy. Both interpretations are analytically significant. The first signals underuse of proven tools. The second signals opacity in AI governance. Critically, both lead to the same policy implication: standardized AI disclosure requirements are needed in public procurement and project reporting.

In addition, conducting verified technical audits across twenty cities would require substantial institutional access and financial resources. This study was conducted without external funding, making such audits unfeasible.

Future research with multi-institutional support is recommended to build a verified AI technique/digital enabler registry, applied by the official sources listed in Appendix L (water utilities, companies, etc.).

C4) Among 142 strategic initiative rows with at least one digital enabler, IoT and sensing infrastructure dominates (101 mentions), followed by cloud computing (62) and big data (37) as the analytics backbone, with digital twins (25) and open data (24) characterizing more mature programs; blockchain is essentially absent (1 mention). Eight multi-digital-enabler initiatives represent the most integrated implementations. A critical limitation is that the 84 regulatory initiatives reference digital enablers only once, confirming a significant policy gap. Future research should estimate the cost of ownership of different digital enabler pathways for tropical urban environments and assess whether a phased IoT-first strategy offers the most feasible entry point for resource-constrained cities like Manaus.

C5) Gate4EcoAI is a multidimensional, queryable evidence-to-policy bridge, with valuable initiatives to support the development of roadmaps for urban water challenges. By linking proven initiative types (e.g., Network Process Control, Quality Monitoring), dominant AI techniques (ML–Anomaly Detection, Supervised ML), and enablers (IoT, Cloud) to real-world statuses, it empowers AI developers, policymakers, utilities, and researchers with evidence-based benchmarking to adapt the best practices locally. For Manaus and analog cities, this structured knowledge base bridges science-to-policy gaps, accelerating resilient water governance amid Amazonian vulnerabilities.

The limitation is that benchmarking alone cannot solve the threats and weakest points of Manaus. Future research should therefore use Gate4EcoAI as the basis for a transferability framework to evaluate governance reform, financing models, institutional readiness, and citizen engagement capacity, so that policy learning focuses not only on what leading cities do but also on the conditions that must be in place for those practices to work in Brazilian Amazon Capital.

Appendices

All figures, files, and appendices are archived in the Harvard Dataverse (Gomes da Silva, 2026).

Appendix A: Basic profile of the Ten International Ranking

Appendix B – AI Techniques

Appendix C – Digital Enablers

Appendix C1 – Basic explanation about AI Techniques and Digital Enablers

Appendix D – Basic Profile of the 265 cities and Performance in the Ten International Ranking

Appendix D1 – Explanation of the ten steps of Phase 3

Appendix E – Performance of 99 Benchmark Smart Sustainable Cities
Appendix F – Main Environmental Areas
Appendix G – Main Goals
Appendix H – Main Initiatives Categories
Appendix I – Status of the Initiatives
Appendix J – Rounds of prompts used for finding initiatives related to water in 20 BSSCs
Appendix L – Initiatives found in 20 BSSCs
Appendix M – Prompt for Generating the HTML page – Dashboard
Appendix M1 – The HTML page - Dashboard
Appendix N – Prompt used to generate the HTML page – AI Technique
Appendix N1 – The HTML page – AI Technique
Appendix O – Prompt used to generate the HTML page – Digital Enablers
Appendix O1 – The HTML page – Digital Enablers
Appendix P – Prompt used to generate the main HTML page – GATE4ECOAI
Appendix P1 – The HTML page – GATE4ECOAI

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