

Article

Visualizing ESG Performance in an Integrated GIS–BIM–IoT Platform for Strategic Urban Planning

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Abstract

As cities confront intensifying environmental challenges and increasing expectations for sustainable governance, extending Environmental, Social, and Governance (ESG) evaluation frameworks to the urban scale has become a pressing need. However, existing ESG systems are typically designed for corporate contexts, lacking city-specific indicators, integrated data representations, and reliable ESG information with high spatial and temporal resolution for informed decision-making. This study proposes a comprehensive ESG evaluation framework tailored to green cities, which consists of three core components: (1) The construction of a green-oriented ESG indicator system with an expert-informed weighting system; (2) the design of a GIS-BIM-IoT integrated ontology that semantically aligns spatial, infrastructure, and observational data with ESG dimensions; and (3) the implementation of a web-based data integration and visualization platform that dynamically aggregates and visualizes ESG insights. A case study involving a primary school and an air quality monitoring station in Hong Kong demonstrates the system's capability to infer material recycling rates and pollution concentration scores using ontology-driven reasoning and RDF-based knowledge graphs. The results are rendered in an interactive 3D urban interface, supporting real-time, multi-scale ESG evaluation. This framework transforms ESG assessment from a static reporting tool into a strategic asset for transparent, adaptive, and evidence-based urban sustainability governance.



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1. Introduction

With the rapid acceleration of globalization and urbanization, sustainable development has garnered increasing global attention. By 2025, it is predicted that approximately 70% of the world's population will reside in urban areas [1]. Cities, as major centres of human activity, dominate the allocation of global resources, accounting for around 75% of total energy consumption [2] and generating over 60% of greenhouse gas emissions [3]. As such, achieving a sustainable balance between energy consumption, environmental protection, economic growth, social well-being, and human health presents an urgent and complex challenge. In this context, the concept of a “green city” has gained prominence. A green city is broadly defined as one that minimizes its environmental impact by reducing waste, lowering emissions, promoting recycling, accelerating the adoption of renewable

energy, and supporting compact urban forms while enhancing open green spaces and fostering sustainable local economies [4]. In response to these global concerns, the United Nations adopted the 2030 Agenda for Sustainable Development in 2015 [1], which outlines 17 Sustainable Development Goals (SDGs). Among them, several goals are directly linked to urban sustainability, including Industry, Innovation and Infrastructure (SDG 9) and Sustainable Cities and Communities (SDG 11). These goals collectively call for coordinated actions across sectors to advance a more sustainable future.

Environmental, Social, and Governance (ESG) factors have emerged as critical dimensions in evaluating sustainable development performance. First proposed by the United Nations in the 2004 Global Compact, ESG has primarily been used to assess the non-financial performance of enterprises [5]. ESG indicators provide a quantifiable framework for measuring corporate sustainability and are widely regarded by investors as essential benchmarks for assessing risk and long-term value. Companies with strong ESG performance are generally more resilient during crises and are thus more attractive to investors [6]. Consequently, ESG plays a key role in promoting sustainable and responsible investment practices.

Despite the growing relevance of ESG in corporate governance, its application in urban-scale sustainability assessment remains limited. Urban environments present unique complexities, including diverse asset types, real-time dynamics, and interlinked physical-social systems, that existing ESG frameworks fail to adequately address. Some scholars have advocated for government-level ESG disclosure as a means of improving transparency, monitoring performance, and strengthening accountability in public governance [7]. However, several significant challenges impede the use of ESG in urban governance contexts: first, although over 170 ESG indicators and more than 120 voluntary reporting standards exist [8,9], these frameworks are largely designed for corporate evaluation and lack city-specific indicators that reflect the spatial, infrastructural, and social complexities of urban systems; second, ESG evaluation relies heavily on high-quality data, but the collection structuring, and integration of reliable environmental, social, and governance data at the city level remains a substantial challenge due to data fragmentation, inconsistencies, and access constraints [7]; third, Urban planners and policymakers are typically more concerned with holistic ESG scores that inform strategic decision-making, rather than the granular values of individual indicators. As a result, current ESG reporting formats, often lengthy, static, and indicator-heavy, either fail to attract sufficient attention from decision-makers or obscure meaningful patterns hidden across individual metrics. Typically, ESG scores follow a hierarchical structure, with an overall score decomposed into Environmental, Social, and Governance dimensions, each further divided into sub-categories (e.g., air quality, energy, water), which are then evaluated based on specific indicators such as PM_{2.5} concentration, energy consumption, or water reuse rate. This highlights the need for intuitive and integrated methods for data representation and visualization.

Building on this vision, the present study seeks to extend ESG-based evaluation from the corporate sphere to the urban scale through the application of state-of-the-art DT technologies. It aligns ESG assessment with the unique requirements and characteristics of green cities and makes three principal contributions:

1. Establishment of a green-city-oriented ESG indicator system: Recognizing the inadequacy of corporate-focused ESG indicators in reflecting the sustainability challenges at the urban scale, this study develops a city-level ESG evaluation index system grounded in international standards such as ISO 37120 [10], the UN-Habitat City Prosperity Index (CPI) [11], and green building certifications. Unlike traditional frameworks that emphasize isolated domains or static evaluation, the proposed system introduces clearly defined indicators across the Environmental, Social, and

Governance dimensions, aligned with urban planning objectives. The weighting mechanism incorporates expert knowledge, which provides informed judgment in situations where large-scale urban datasets are lacking. This ensures the evaluation system is both grounded in professional insight and practically relevant, thereby enhancing its capacity to guide local strategy formulation.

2. Design of an integrated semantic data model for ESG assessment: Existing urban sustainability frameworks often suffer from fragmented data representations and lack a common structure to interconnect physical infrastructure, environmental conditions, and social services. This study addresses this gap by designing a semantically integrated data model that bridges ESG indicators with established GIS, BIM, and IoT data structures. The model defines a set of unified types, attributes, and relational schemas that enable multi-domain knowledge representation. This integration not only enhances data interoperability across sectors but also establishes a formal foundation for reasoning and indicator inference, overcoming the semantic inconsistency and data silos prevalent in traditional urban data systems.
3. Implementation of a real-time, multi-scale ESG evaluation and visualization framework: This study implements a unified evaluation framework to address the limitations of existing ESG systems, which often rely on static and fragmented data, making them inadequate for capturing the dynamic and multi-scale nature of urban sustainability. The proposed framework enables the continuous integration of heterogeneous data sources across spatial, semantic, and sensor dimensions, transforming them into actionable ESG insights. By combining semantic enrichment with real-time visualization, the system not only supports up-to-date, location-aware indicator inference but also provides decision-makers with interactive, multi-scale ESG assessments, thereby shifting ESG evaluation from a passive reporting tool to a strategic instrument aligned with the evolving demands of green city governance.

The structure of this paper is as follows. Section 2 reviews existing urban sustainability assessment frameworks and the current efforts to extend ESG concepts into GIS and BIM models. Section 3 presents the research methodology and technical roadmap. Section 4 showcases a practical case study to validate the proposed approach. Finally, Section 5 discusses the contributions of this research and outlines potential directions for future work.

2. Literature Review

2.1. Digital Twin Application in ESG

The rapid advancement of digital-twin (DT) technology has significantly accelerated the integration of ESG principles into urban governance. A digital twin was originally defined as “a set of virtual constructs that fully describes a potential or actual physical product from the micro-atomic level to the macro-geometric level [12].” It comprises three essential elements: (i) a physical space, (ii) a virtual space, and (iii) bidirectional, real-time data flows that connect the two [13]. Within an urban context, DT applications leverage Geographic Information System (GIS), Building Information Modeling (BIM), and Internet of Things (IoT) to collect, integrate, and analyze city-scale information. BIM—widely regarded as a disruptive technology in the AECO sector—offers a unified three-dimensional database that records all project information across the entire building life cycle [14]. GIS, as a multifunctional decision-support system, represents the real world by linking spatial references with rich semantic attributes [15]. Complementing these, the IoT layer, comprising dense networks of sensors and actuators, continuously senses the urban environment and streams high-frequency data into the virtual space [16]. By fusing GIS and BIM, DT can translate physical urban artifacts, such as buildings, infrastructure, and public spaces, into geo-referenced 3D virtual models. These models provide a unified data structure that stores

ESG-related information natively in digital form rather than in disparate physical files. Simultaneously, the IoT network automatically captures and writes real-time observations to the 3D models, thereby enabling a truly data-driven, city-level ESG evaluation system.

Emerging studies have begun to explore DT-enabled ESG analytics [17]. For instance, Dovolil and Svitek [18] employ existing urban IoT assets, such as sensors, GPS, mobile devices, and cameras, to acquire environmental-quality, transport, and public-health data, which are then used to estimate carbon emissions and social-equity indicators. Wu and Alias's [19] systematic review demonstrates that BIM can evaluate energy consumption, carbon emissions, construction safety, and governance processes throughout the entire building life cycle. Barykin et al. [20] digitize urban logistics networks to quantify ESG outcomes such as emission reduction, transparency, and governance efficiency. Recent research has also begun to explore city-scale digital twins with stronger cross-sectoral integration. For instance, a series of studies by the same research group has investigated resilience-oriented urban energy twins. Their initial work emphasized cross-regional energy sharing and the coupling of buildings with e-mobility networks in the Greater Bay Area, demonstrating how such linkages can improve distribution efficiency and adaptive capacity [21]. Building on this foundation, their subsequent studies proposed integrative frameworks for urban energy networks and developed city information models that combine electric vehicles, charging stations, buildings, and the power grid through agent-based modeling. Their findings suggest that incorporating multiple uncertainty factors not only improves energy efficiency but also enhances the resilience of urban electricity systems [22,23].

Nevertheless, these efforts exhibit two notable limitations: (1) They typically address a single functional domain, such as transport, construction, or logistics, rather than the city as an integrated whole; (2) they focus on isolated pilot projects and do not provide a generalized data model that can be replicated across different urban settings; and (3) they rely predominantly on retrospectively collected, file-based data rather than a proactive capture model. This delays availability when decisions are due, keeps datasets in silos, and weakens links across indicators.

2.2. Urban Sustainability Assessment Frameworks

Urban sustainability assessment has increasingly relied on a diverse array of frameworks designed to measure performance across environmental, social, and governance (ESG) dimensions. Among the most widely recognized is ISO 37120, which provides standardized indicators for city services and quality of life. Developed by the International Organization for Standardization, ISO 37120 establishes a comprehensive yet flexible benchmarking system, covering domains such as air quality, public transport, waste management, education, and urban safety. Its emphasis on comparability and data-driven governance makes it a cornerstone for ESG-informed urban reporting. In contrast to ISO 37120, which prioritizes fundamental service provision, ISO 37122 [24] concentrates on innovation and technology-enhanced urban competencies, including intelligent infrastructure, data-informed governance, and the integration of information and communication technology (ICT). These characteristics are especially pertinent to ESG oversight and environmental monitoring within the framework of smart cities. Complementing ISO 37120, the CPI offers a broader framework, incorporating productivity, infrastructure development, quality of life, equity, environmental sustainability, and urban governance. The CPI serves both as a diagnostic and strategic planning tool, embedding social inclusion and resilience more explicitly within the sustainability discourse.

At the building and neighborhood scale, LEED v4.1 [25], BREEAM [26], and China's Assessment Standard for Green Building (GB/T 50378) [27] play crucial roles in operationalizing ESG principles in the built environment. LEED v4.1, developed by the U.S.

Green Building Council, emphasizes carbon reduction, energy and water efficiency, and stakeholder engagement. BREEAM, originally from the UK, introduces flexible criteria that can be tailored to local contexts while maintaining a performance-based approach. The GB/T 50378 standard incorporates Chinese-specific environmental and social indicators, focusing on passive design, ecological protection, and public health.

Although existing frameworks have been widely adopted in practice, they still present notable limitations, particularly in terms of indicator fragmentation and the absence of reliable, coordinated, and dynamic data systems. Recent studies, such as that by Gavaldà et al. [28], have highlighted the importance of adopting more adaptive and integrated approaches. They propose a combination of traditional performance-based indicators, such as ISO 37120, with well-being-oriented frameworks like the CPI, which introduces key indicators related to equity, accessibility, and governance transparency. Since this research focuses on green city development, reference is also made to established green building evaluation systems, including LEED, BREEAM, and GB/T 50378, which offer valuable perspectives on environmental performance at the building and community levels. The integration of ESG perspectives into urban sustainability frameworks depends on improved data interoperability and the adoption of dynamic indicators. To support this goal, it is essential to build upon existing digital infrastructures, define standardized data flows and specifications, and establish clear mappings between ESG-related indicators. These steps can enhance the practicality and reliability of implementing ESG-oriented sustainable city strategies.

2.3. Heterogeneous Data Integration

The integration of various sources of data, as well as the dynamic visualization of multi-scale urban datasets, remains a key challenge for sustainable city strategy development. This complexity is most evident in the integration of GIS and BIM data, both of which are structurally rich, large-scale, and grounded in distinct disciplinary schemas (e.g., geotechnics, construction) [29]. A set of works have attempted to fulfill this industry gap. The most popular and intuitive approach is to map data between CityGML [30] and Industry Foundation Class (IFC) [31], which are dominant standards in their respective industries [32]. CityGML uses Boundary Representation (B-rep) to explain geometry properties in XML schema, whereas IFC adopts Swept Solid, Constructive Solid Geometry (CSG), and B-rep in EXPRESS schema [33]. Moreover, the semantic information between them varies a lot in each hierarchy. For instance, the building information in CityGML only contains basic elements such as doors and windows, while IFC encompasses more family categories [34]. A GeoBIM extension has been developed that appends IFC data into CityGML context [33]. The bi-directional conversion between IFC and CityGML is achieved by developing a unified data model (UDM) that minimizes the data loss during transformation. Yuan and Shen [35] extend the IFC standard to interoperate both GIS and BIM data. Deng et al. [36] propose a mapping approach in different levels of detail using schema mediation and instance comparison.

However, as indicated by Liu et al. [37], the conversion between CityGML and IFC causes semantics loss and geometry mis-translation due to their distinct properties. In addition, while these approaches focus mainly on object-level or building-level coordination, they fall short of supporting city-scale semantic modeling, which is essential for ESG-informed policy-making. Here, semantic modeling at the city scale refers to representing heterogeneous urban data, such as buildings, infrastructure, public assets, and sensor observations, within a coherent structure that preserves meaning across domains and scales. Shi et al. [38] proposed an ontology-driven methodology to form a semantically rich City Information Model (CIM), which harmonizes urban data by structuring it into hierarchical

classes like Facility, Element, and Feature, which encapsulate buildings, infrastructures, and public assets with semantic coherence across different Levels of Detail (LoDs). Apart from GIS and BIM data, the integration of dynamic IoT data are surveyed by Tang et al. [33] and Isikdag [39]. IoT data, ranging from air quality sensors to occupancy and energy consumption logs, are not treated as supplementary layers but are semantically integrated via Brick and SSN/SOSA ontologies. These ontologies semantically associate real-time observations with physical and logical entities defined in the ontology structure, thereby enabling continuous tracking of ESG-related indicators such as carbon emissions, thermal comfort, and urban heat island effects. This enriched semantic model allows stakeholders to conduct cross-scale ESG queries, simulate policy impacts, and derive actionable intelligence for sustainable urban governance. Furthermore, most urban DT implementations are not designed with ESG as a first-order requirement. ESG-specific assets and records such as water-quality monitoring stations, ICT service performance, permitting logs, and procurement records are often not defined as first-class entities at design time and are therefore omitted from the scope of the twin. As a result, important evidence streams for ESG oversight are difficult to integrate and hard to query across domains.

To support such modeling, this study re-categorizes urban indicators into three semantic tiers: (1) GIS-based indicators shaped by terrain, land use, or spatial zoning; (2) BIM-based indicators derived from asset design, material use, or energy modeling; and (3) IoT-based indicators continuously captured through real-time sensing. By unifying these data streams into a semantic knowledge base, the CIM-based framework lays a solid foundation for developing ESG-aligned, interoperable, and scalable data infrastructures for smart cities.

In summary, DT technologies have increasingly been recognized as enablers for integrating ESG principles into sustainable urban development. However, existing research predominantly focuses on specific operational domains rather than addressing ESG integration at the holistic city scale. While various ESG-related frameworks such as ISO 37120, the UN-Habitat CPI, and green building certification offer structured guidance, they often operate in isolation, lack the dynamic, interconnected data infrastructure required for real-time ESG governance, and do not provide a proactive, standards-based mechanism for capturing ESG-relevant data streams. To bridge this gap, this study aims to develop an ESG-oriented evaluation system tailored to green cities, with the goal of supporting sustainability planning. Drawing from existing urban sustainability frameworks and green building rating systems, the proposed ESG system emphasizes adaptability, interoperability, and data-driven decision-making. Its implementation depends on the design of a standardized and dynamic data flow that can continuously capture heterogeneous data and update ESG-relevant indicators. Achieving this requires the semantic integration and extension of existing GIS and BIM data models, enriched by real-time IoT observations.

3. Approach for Semantic Modeling and Data Integration of ESG Indicators in Green Cities

This section presents a three-component methodological framework designed to enable transparent, automated, and semantically driven ESG evaluation in the context of green cities. Component 1 establishes a green city-oriented ESG evaluation system tailored to the urban scale. Based on established international frameworks and local sustainability priorities, a structured set of ESG indicators is defined across environmental, social, and governance dimensions. These indicators are further quantified and weighted using a multi-criteria expert-informed mechanism, enabling composite ESG scores that are both interpretable and actionable for policymakers. Component 2 constructs an ESG-driven semantic ontology based on GIS–BIM–IoT integration. The ontology is structured into

three layers: a foundational layer reusing standards such as CityGML, IFCOWL [40], and SOSA/SSN [41]; an ESG-specific semantic extension layer; and a rule-based reasoning layer that enables automated computation of ESG indicators. This semantic backbone facilitates cross-domain interoperability and supports traceable, explainable indicator evaluation. Component 3 implements the data integration pipeline that enables real-time ESG assessment in a web-based spatial environment. Through the transformation of IFC models into RDF and glTF formats and the incorporation of real-time IoT sensor data via web APIs, spatial, semantic, and temporal data streams are unified. This ensures synchronized representation and interactive visualization of ESG indicators across urban spaces. Together, these three components form an intelligent, interoperable framework to support evidence-based ESG governance in green cities. Figure 1 illustrates the interactions among the three components.

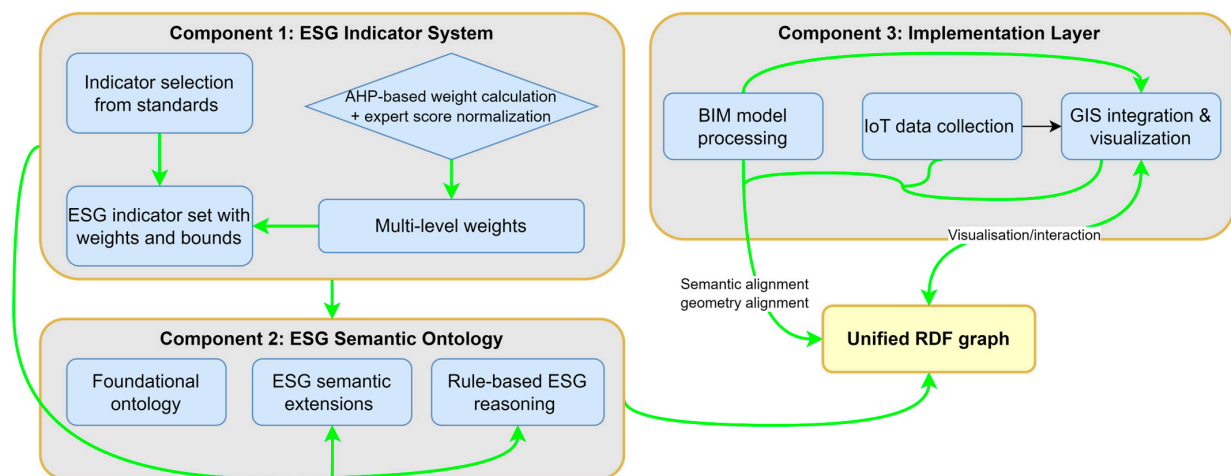


Figure 1. A three-component framework for ESG indicator evaluation and visualization (The blue boxes represent the three main components and the yellow box denotes the unified RDF graph).

3.1. Component 1: Green-Based City-Scale ESG Evaluation

3.1.1. ESG Indicator Modeling and Binding

To develop data-driven ESG indicators for green cities, a multi-stage indicator identification and screening process was conducted. The process began with a systematic review of items from the ISO 37120 standard that were directly relevant to ESG dimensions. Selection was guided by three criteria: (1) reflecting long-term sustainability outcomes rather than short-term outputs; (2) being quantifiable at the city or regional scale; and (3) aligning conceptually with the goals of environmental protection, social equity, and transparent governance. Importantly, the selected indicators also align with key targets of SDG 11 (Sustainable Cities and Communities), which emphasize inclusive, safe, resilient, and sustainable urban development. To ensure comprehensive coverage of smart city and sustainable urban development themes, the initial indicator pool was expanded by incorporating additional indicators from ISO 37122 and the UN-Habitat CPI. Selection at this stage focused on (1) complementarity with ISO 37120, particularly in addressing gaps related to digitalization and social inclusion, and (2) the potential for indicators to be supported by dynamic, real-time, or spatially disaggregated data.

To further enrich the indicator set and align it with established best practices in sustainable building and urban planning, relevant ESG-related items were identified and integrated from three authoritative green building frameworks: LEED v4.1, BREEAM, and GB/T 50378. These frameworks provide detailed, design-oriented assessment criteria that emphasize the environmental, social, and governance performance of individual buildings and sites. Selected indicators prioritized: (1) Spatial attribution at the building or block level,

such as energy intensity and material reuse; (2) emphasis on performance outcomes rather than prescriptive design intent, such as measured energy efficiency; and (3) cross-scalar relevance, enabling applicability at both the project and city levels. Through these three stages of indicator selection and refinement, a comprehensive and implementation-ready ESG monitoring framework has been constructed to support multi-scale sustainability assessment in urban contexts.

Since the goal is to develop a data-driven ESG framework, an additional selection phase was carried out to identify indicators from the integrated ESG library that can be supported by GIS, BIM, and IoT technologies. This step ensures the practical feasibility of automatic or semi-automatic data collection and monitoring in real-world urban environments. The selection focused on indicators that can be mapped, sensed, or modeled using existing digital infrastructure and platforms. Three key aspects were considered: (1) Whether the indicator reflects spatial characteristics and can be geolocated and quantified within a GIS environment, such as per capita green space and land use mix; (2) whether the indicator can be derived from BIM models, particularly building attributes such as envelope materials and green roof coverage; and (3) whether the indicator is measurable through IoT devices, such as real-time air quality and energy consumption. This additional selection phase does not alter the conceptual structure of the previously established ESG framework but instead facilitates the development of a customized data model based on existing GIS, BIM, and IoT infrastructures. It enables the creation of a scalable, real-time, and interoperable ESG monitoring environment aligned with digital twin technologies. The initial selection of ESG indicators, from ISO 37120, ISO 37122, CPI, LEED v4.1, BREEAM, and GB/T 50378, along with their respective sources, is provided in Appendix A for reference. Table 1 presents a subset of these indicators that are specifically relevant to green cities and indicates their suitability for integration into data models based on GIS, BIM, and IoT technologies.

Table 1. ESG indicators and classification.

ESG	Sub-Category	Indicator	GIS-BIM-IoT Relevant	Unit	Min	Max	f _m
Environment	Air Quality	Fine particulate matter (PM _{2.5}) concentration	T	µg/m ³ (annual mean)	5	35	1.2909
		PM ₁₀ concentration	T	µg/m ³ (annual mean)	15	70	1.2955
		NO ₂ concentration	T	µg/m ³ (annual mean)	10	40	1.2037
		SO ₂ concentration	T	µg/m ³ (24 h mean)	40	125	1.3477
		O ₃ concentration	T	µg/m ³ (8 h mean, peak season)	60	100	1.2612
		CO concentration	T	µg/m ³ (24 h mean)	4	7	1.3845
		Number of days with unhealthy air quality	T	days/year	0	30	1.2498
		Number of real-time ICT-based air quality monitoring stations per 100,000 population	T	numbers	0	1	0.8528
		Compliance rate of air quality	T	%	0	100	1.2089

Table 1. Cont.

ESG	Sub-Category	Indicator	GIS-BIM-IoT Relevant	Unit	Min	Max	f _m
Environment	Climate and Energy	Greenhouse gas emissions measured in tons per capita	T	tCO ₂ e /person/year	0.5	20	0.9981
		Percentage of total energy derived from renewable sources	T	%	0	70	1.0345
		Energy consumption of public buildings per year	T	kWh/m ² /year	100	350	0.8178
		Percentage of building energy from renewable sources	T	%	0	100	0.9997
		Total electrical energy use per capita	T	kWh/person/year	40	50,000	0.8544
		Energy from wastewater treatment per capita	T	kWh/person/year	30	400	0.9138
		Energy from solid waste per capita	T	kWh/person/year	10	150	0.9918
		Percentage of energy from decentralized production systems	T	%	0	35	0.8199
		Storage capacity of the energy grid per capita	T	kWh/person	0.05	0.6	0.8799
		Percentage of public street lighting in total municipal energy consumption	T	%	15	50	0.7912
		Percentage of street lighting refurbished	T	%	0	100	0.7071
	Green Infrastructure	Green area (hectares) per 100,000 population	T	hectares	60	800	0.9186
		Annual number of trees planted per 100,000 population	T	numbers	100	20,000	0.8226
		Percentage of buildings with green roofs	T	%	0	65	0.9071
		Percentage of public landscape areas with permeable or natural materials	T	%	20	80	0.9013
		Kilometers of bicycle paths and lanes per 100,000 population	T	kilometres	5	70	0.8639
		Buildings built/refurbished in last 5 years conforming with green building principles	T	%	15	80	0.8933
		Percentage of public buildings requiring renovation/refurbishment (by floor area)	T	%	1	20	0.8464
	Waste and Water	Percentage of the city population with waste drop-off centres equipped with telemetering	T	%	20	50	1.1782
		Percentage of the city's solid waste that is recycled	T	%	5	85	1.1828
		Percentage of treated wastewater being reused	T	%	0	85	1.1254
		Percentage of reused/recycled construction materials in new buildings	T	%	0	25	0.8851
		Percentage of city population with sustainable access to an improved water source	T	%	10	100	1.1352
		Percentage with telemetering-equipped waste drop-off centers	T	%	20	70	0.9200
		Percentage with door-to-door garbage collection + telemetering	T	%	10	80	0.8826

Table 1. Cont.

ESG	Sub-Category	Indicator	GIS-BIM-IoT Relevant	Unit	Min	Max	f _m
Environment	Waste and Water	Percentage of drinking water under real-time quality monitoring	T	%	10	80	1.0930
		Annual hours of water service interruption per site	T	hours	0	45	0.9686
		Compliance rate of wastewater treatment	T	%	10	100	1.3705
		Compliance rate of water quality	T	%	30	90	1.4293
	Biodiversity and Environment	Hazardous Waste Generation per capita (tonnes)	T	tonnes	0	1	1.0842
		Percentage change in number of native species	F	%	30	90	1.1154
		Annual frequency of ecosystem remote sensing monitoring	T	days/year	12	60	0.9625
Social	Health and Livability	Life expectancy	F	years	55	85	1.1598
		Under-age-five mortality per 1000 live births	F	‰	5	100	1.2673
		Square meters of public outdoor recreation space per capita	T	m ²	2	25	0.9408
		Noise pollution	T	dB	30	60	1.0304
		Percentage of population registered with air and water quality alert systems	T	%	0	100	0.9269
		Percentage of natural-hazard-related deaths per 100,000 population	T	%	0	20	1.1700
		Percentage of deaths by industrial accidents per 100,000 population	T	%	0	25	1.1767
		Percentage of annual expenditure on emergency management planning	F	%	5	15	1.1319
		Percentage of buildings meeting thermal comfort standards	T	%	10	50	0.9414
		Percentage of buildings with optimized natural lighting	T	%	10	50	0.8572
	Mobility and Access	Percentage of buildings with certified acoustic performance	T	%	10	50	0.8503
		Percentage of buildings with continuous IAQ monitoring	T	%	5	50	0.8984
		Annual number of public transport trips per capita	T	trips	30	560	0.9051
		Percentage of commuters using a travel mode other than a personal vehicle	T	%	20	70	0.9522
		Percentage of city area mapped by real-time interactive street maps	T	%	28	80	0.8380
		Percentage of city streets with real-time traffic alerts	T	%	20	80	0.9535
		Percentage of traffic lights that are intelligent/smart	T	%	5	50	0.9644
		Area of site with internet connections	T	%	20	80	1.1814
		Percentage of city area covered by municipally provided Internet	T	%	40	70	1.1814
		Average downtime of city's IT infrastructure per year	T	hours	0	48	1.1539

Table 1. Cont.

ESG	Sub-Category	Indicator	GIS-BIM-IoT Relevant	Unit	Min	Max	f _m
Social	Housing and Equity	Percentage of city population living in dwellings that are under registered tenure	T	%	50	95	0.8633
		Percentage of city population living in slums	T	%	5	50	0.9755
		Average Living Area per Capita	T	m2	10	60	0.9590
		Number of homeless per 100,000 population	F	%	0	400	1.0589
		Percentage of households with smart electricity meters	T	%	5	90	0.8086
		Percentage of households with smart water meters	T	%	5	90	0.8115
Governance	Participation	Voter participation in last municipal election	F	%	20	90	0.9681
		Civic Participation	F		0.2	0.9	0.9389
	Transparency	Number of convictions for corruption and/or bribery by city officials	F	numbers	10	90	0.9871
		Existence of open government data platform	F	scores	0	10	1.0184
		Access to Public Information	F	%	0	100	1.0598
	Policy and Planning	Existence of participatory budgeting mechanisms	F	%	2	10	1.0306
		Existence of a public climate action plan	F		0	1	1.0310
		Green Spending Share	F	%	10	45	1.1075
		Land Use Efficiency	T	ratio	0	3	0.9389
		Land Use Mix	T		0	1.61	0.9317
		Annual number of citizens engaged in urban planning per 100,000	F	numbers	100	2000	0.8741
		Average time for building permit approval	T	days	20	200	0.7634
		Percentage of buildings certified under recognized green building standards	F	%	10	50	0.9803
		Percentage of sites delivered to full BIM	T	%	0	70	0.9112
		Local Expenditure Efficiency	F		0	200	0.9683
	Fiscal Governance	Percentage of municipal budget spent on smart city innovations and initiatives per year	F	%	0	3	1.0000

3.1.2. Analytic Hierarchy Process (AHP) Based ESG Weighting Framework

To develop an ESG weighting framework, especially in the context of insufficient city-level performance data, this study designs a two-stage hierarchical weighting framework for ESG indicators, combining the Analytic Hierarchy Process (AHP) with a structured expert scoring method to determine the relative importance of ESG dimensions and their sub-indicators. AHP, proposed by American operations researcher Saaty in the early 1970s, is a subjective weighting method for multi-criteria decision analysis [42]. Its standard structure includes a goal layer, a criteria layer, and an alternatives layer. In this study, the structure is simplified to include only a goal layer and a single-level criteria layer, using expert judgment to compare the relative importance among criteria.

The entire weight calculation process consists of the following four steps:

Step 1: Construct the evaluation indicator system.

Clarify the structure and components of the criteria layer and identify the indicators to be evaluated, totaling n items.

Step 2: Determine the order of the judgment matrix.

According to the number of indicators in the criteria layer, construct an $n \times n$ judgment matrix A as shown in Equation (1). Each element a_{ij} in the matrix represents the relative importance of indicator i compared to indicator j .

Step 3: Obtain expert judgments and aggregate them into a group judgment matrix.

Invite k experts to perform pairwise comparisons of the indicators using Saaty's 1–9 scale (see Appendix B), resulting in k individual judgment matrices. Subsequently, use the geometric mean method to aggregate all individual matrices into a final group judgment matrix [42], as calculated in Equation (2).

Step 4: Calculate weights and perform consistency checks.

This study adopts the Row Geometric Mean Method (RGMM) to derive the weight vector from the judgment matrix. RGMM is a widely used prioritization method in AHP, known for its low computational complexity and suitability for group decision-making [43]. The detailed calculation is shown in Equations (3) and (4): the geometric mean of each row is first computed, followed by normalization to obtain the final weights of all indicators. To assess the logical consistency of the judgment matrix, the Geometric Consistency Index (GCI) is introduced. This index was proposed by Crawford and Williams in 1985 specifically to evaluate the consistency of weight vectors derived using RGMM [44]. For example, given three indicators, A_1 , A_2 , and A_3 , if the judgments indicate that A_1 is more important than A_2 and A_2 is more important than A_3 , then by transitivity, A_1 should also be more important than A_3 . If the actual judgment ranks A_3 above A_1 , a logical inconsistency exists in the matrix. When $GCI < 0.037$ and the number of indicators $n \leq 9$, the judgment matrix is generally considered to have acceptable consistency. The computation of GCI is presented in Equation (5).

$$A = (a_{ij})_{n \times n} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \quad (1)$$

where:

$$a_{ij} > 0, a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1$$

$$a_{ij}^{(group)} = \left(\prod_{e=1}^k a_{ij}^{(single)} \right)^{1/k} \quad (2)$$

$$w'_i = \left(\prod_{j=1}^n a_{ij}^{(group)} \right)^{1/n} \quad (3)$$

$$w_i = \frac{w'_i}{\sum_{i=1}^n w'_i} \quad (4)$$

$$GCI = \frac{2}{(n-1)(n-2)} \sum_{i < j} \left(\ln a_{ij}^{(group)} - \ln \frac{w_i}{w_j} \right)^2 \quad (5)$$

This simplified AHP approach is applied at two levels within the weighting framework. In the first stage, the relative importance of the three primary ESG dimensions, Environmental, Social, and Governance, is first evaluated. Subsequently, more detailed assessments are conducted for the sub-categories under each dimension, as shown in

Table 1, to extract their relative weights within each dimension. To support this process, a structured interview approach was employed to consult nine experts from the domains of urban planning, sustainable development, digital cities, and urban transportation. Based on their professional insights, the experts conducted pairwise comparisons of the ESG dimensions and their respective sub-categories, forming the basis for the subsequent weight calculations.

The second stage focuses on the allocation of weight to each indicator within each ESG dimension. Initially, the same group of experts was invited to score each indicator using a five-point Likert scale across three evaluation factors: impact, urgency, and scope of impact. To reduce cognitive load and enhance clarity, the “impact” factor was further categorized into positive impact and negative impact, with relevant indicators grouped accordingly. For both “impact” and “urgency,” a score of 1 indicates the lowest degree and 5 the highest. For “scope,” a score of 1 indicates impact limited to individuals, 3 indicates impact at the community or district level, and 5 denotes city-wide impact, with 2 and 4 representing transitional levels.

The expert scores were first normalized for each factor. The normalized scores for each indicator were then averaged across all experts to obtain a consolidated standardized score s_{mf} for each evaluation factor f . Subsequently, an AHP-based pairwise comparison was conducted to determine the relative importance of the three factors themselves, resulting in a weight vector w_f . Finally, as shown in Equation (6), the overall weight of each indicator was calculated as the weighted sum of its normalized scores across the three factors, multiplied by their respective weights.

$$w_m = \sum_{f=1}^3 s_{mf} \times w_f \quad (6)$$

To enable unified evaluation across heterogeneous ESG indicators with diverse units and scales, a quantitative scoring scheme is established to normalize all input indicators and aggregate them into structured ESG sub-scores and a composite score.

3.1.3. Indicator Normalization and Quantification

A unified scoring mechanism is established by normalizing each indicator based on the computational methodology adopted in the CPI [11], thereby enhancing the system’s comparability and operability. The score for each indicator ranges from 0 (indicating the worst performance) to 1 (indicating the best performance) [45]. Specific scores are assigned based on the actual (or predicted) value of the indicator within a predefined interval, following the rules below:

For positive indicators (where a higher value indicates better performance)

$$Score_p = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

For negative indicators (where a lower value indicates better performance)

$$Score_n = \frac{x_{max} - x}{x_{max} - x_{min}} \quad (8)$$

If the actual value falls outside the defined range, a full score (1) or a zero score (0) is assigned, depending on whether the indicator is positive or negative.

To ensure the objectivity of the green city operation assessment and provide insights for strategy optimization, the maximum and minimum values for each indicator should meet two criteria: (1) Data are primarily sourced globally to avoid regional bias; and

(2) sources must be authoritative and verifiable to ensure data authenticity and accuracy. These reference values are presented in Table 1 to ensure transparency and reproducibility in the normalization process.

Specifically, the determination of indicator value ranges relies on the following three types of sources:

1. Recommended values or thresholds from international or national standards. For example, pollutant concentration indicators (such as PM_{2.5}, PM₁₀, and NO₂) in the air quality category are based on the WHO Global Air Quality Guidelines [46].
2. Historical statistical data from authoritative databases, including those maintained by the United Nations, World Bank, OECD, and IEA. For instance, indicators under the governance category, such as “open government”, “access to public information”, and “average time for building permit approval”, are sourced from World Bank datasets.
3. Survey data from reputable industry reports. For example, the indicator “percentage change in number of native species” is derived from WWFs 2024 Living Planet Report [47].

For certain indicators that lack unified international standards or comprehensive global statistics, an alternative estimation approach is adopted. For example, the indicator “percentage of municipal budget spent on smart city innovations and initiatives per year” is calculated based on the methodology outlined in ISO 37122, using the ratio of ICT-related spending to the total municipal expenditure. Although comprehensive global data are unavailable, reference values were obtained from Mainland China, Hong Kong, Singapore, and the UK, which are recognized for their relatively advanced levels of smart city development [48]. Among them, Singapore reported the highest ICT spending ratio at 2.69%, which serves as a reasonable upper bound for this indicator. Accordingly, the value range is set from 0 to 3.

As this study does not use city-specific calibration datasets, normalization thresholds are initialized from globally applicable benchmarks, such as authoritative guidelines or literature-based ranges. These act as default bounds to maintain cross-region comparability. After deployment in a given city, the platform updates thresholds from local data, such as empirical distributions and declared policy targets, while retaining global defaults as references. To limit regional bias, peer-group calibration (e.g., by climate zone or city size) is supported, and the sensitivity of indicator scores to alternative thresholds is reported.

Based on the above scoring rules, a standardized score can be obtained for each indicator. In addition, a three-tier weighting structure has already been established, comprising the weights of the top-level ESG dimensions (w_{esg}), sub-category weights (w_{sub}), and individual indicator weights (w_m). To avoid distorting the final ESG score through the compounding effect of raw weights, the original weights are not directly multiplied with the standardized scores. Instead, each weight is normalized by dividing it by the average weight of its respective tier, resulting in a scaling factor (adjustment coefficient). These scaling factors (f_{esg} , f_{sub} , and f_m) represent the relative importance of each dimension, sub-category, and indicator, while preserving the semantic range and comparability of the original scores. The computation of these scaling factors is detailed in Equation (9). As shown in Equation (10), the final ESG score for a given city or region is derived by multiplying each standardized indicator score by the product of its corresponding scaling factors and aggregating the results across all tiers.

$$\begin{aligned}
 f_{esg}(a) &= \frac{w_{esg}(a)}{\bar{w}_{esg}} = w_{esg}(a) \times n_{esg} \\
 f_{sub}(s) &= \frac{w_{sub}(s)}{\bar{w}_{sub}} = w_{sub}(s) \times n_{sub} \\
 f_m(i) &= \frac{w_m(i)}{\bar{w}_m} = w_m(i) \times n_{ind}
 \end{aligned} \tag{9}$$

$$ESG^{(S)} = \sum_a f_{esg}(a) \times \sum_{s \in Sub(a)} f_{sub}(s) \times \sum_{i \in Ind(s)} f_m(i) \cdot Score(i) \quad (10)$$

3.1.4. Determination of Weighting System

A purposive sampling strategy was adopted to ensure coverage of the domains implicated by the ESG framework and the GIS–BIM–IoT pipeline. Inclusion criteria required: (a) alignment with at least one area among urban planning, sustainable development, digital cities, or urban transportation; (b) relevant technical experience spanning GIS/BIM/IoT data or ESG assessment; and (c) city-scale exposure, such as participation in municipal programs, standards, or large infrastructure projects. To mitigate individual bias and secure domain coverage, nine experts were engaged rather than a minimal panel of two or three. Pairwise comparisons supplied by each expert were quality-checked using GCI. Across all levels, GCIs of 0.0102, 0.0119, 0.00441, 0.0330, and 0.0256 satisfy the acceptance criterion ($GCI < 0.037$ for $n \leq 9$), indicating internally consistent judgments and supporting the stability of the aggregated priorities. While the panel may not fully represent all ESG-related disciplines, the resulting priorities exhibit strong internal consistency and provide a sound basis for the current weighting framework. The results indicate a pronounced environmental priority in the green-city context, a strong social emphasis on public health and livability, and a governance emphasis on transparency.

At the top ESG level, Environmental carries the greatest relative importance, as shown by the weights Environmental = 0.5259, Social = 0.2369, and Governance = 0.2372, and by the corresponding scaling coefficients Environmental = 1.5777, Social = 0.7107, and Governance = 0.7116. The GCI for this level is 0.0102, which is below the threshold ($GCI < 0.037$ for $n \leq 9$).

Within dimensions, subcategory weights and coefficients are obtained in the same way. In the Environmental dimension ($GCI = 0.0119$), the weights are Air Quality = 0.3432, Climate and Energy = 0.2158, Green Infrastructure = 0.1680, Waste and Water = 0.1860, and Biodiversity and Environment = 0.0869, with corresponding scaling coefficients of 1.7160, 1.0790, 0.8400, 0.9300, and 0.4345, respectively. This pattern reflects the view that, at the city scale, air quality most directly indicates health risks and management performance. In the Social dimension ($GCI = 0.00441$), Health and Livability = 0.5707, Mobility and Access = 0.1871, and Housing and Equity = 0.2422, giving scaling coefficients of 1.7121, 0.5613, and 0.7266. Outcomes related to environmental exposure and population health receive the highest weight. In the Governance dimension ($GCI = 0.0330$), Participation = 0.2285, Transparency = 0.3819, Policy and Planning = 0.2554, and Fiscal Governance = 0.1342, corresponding to scaling coefficients of 0.9140, 1.5276, 1.0216, and 0.5368. Transparency is treated as a foundational capacity for data openness, accountability, and cross-domain coordination.

At the indicator level, the factor weights for the three evaluative factors, Negative/Positive Impact, Urgency, and Scope of Impact, derived from expert judgments are Urgency = 0.4105, Negative/Positive Impact = 0.3742, and Scope of Impact = 0.2153, with $GCI = 0.0256$, indicating acceptable consistency. For each indicator, its weight is calculated as the weighted sum of its normalized factor scores using Equation (6) and then converted to an indicator-level scaling coefficient to ensure that the mean coefficient within each subcategory equals 1. The scaling coefficient for each indicator is reported in Table 1.

3.2. Component 2: Ontology Design for ESG-Driven Green City Evaluation Based on GIS-BIM-Iot

To support data-driven evaluation and integration of urban ESG indicators and enable cross-domain analysis, this study constructs a GIS-BIM-IoT-based semantic ontology system for green cities. This ontology framework bridges heterogeneous data through top-level concepts and logical structures. In recent years, standardized and integrated 3D semantic

city models have been demonstrated as effective information carriers for meeting diverse urban needs [49]. Following the principles of interoperability, extensibility, and semantic clarity, and inspired by the City Information Modeling (CIM) methodology proposed by [38], the proposed ontology is structured into three layers: (1) foundational ontology construction based on existing standards; (2) application-specific semantic extensions aligned with ESG indicators; and (3) rule-based reasoning capabilities.

3.2.1. Foundational Ontology Construction

The foundational ontology serves as the first layer, integrating GIS, BIM, and IoT domains to support consistent and interoperable semantic representation of spatial entities and sensor observations. Ontologies typically distinguish between three fundamental components that underpin their structure. Classes define categories of entities such as buildings, facilities, or spatial zones. Object properties represent semantic relationships between entities, such as *hasPart*, capturing component hierarchies. Data properties describe literal or quantitative values like material area, air pollutant concentration, or geographic coordinates. The design encompasses three aspects: GIS-BIM semantic modeling, IoT semantic integration, and ontology-level semantic mapping. The semantic mapping layer aligns heterogeneous concepts from multiple domain ontologies, enabling cross-standard interoperability by translating terms, relationships, and data structures into a unified semantic framework. Figure 2 illustrates the core class structure of the foundational ontology, showing how they are semantically connected through key object properties such as *hasElement*, *hasLocation*, and *hasObservation*. As shown in the figure, the ontology is organized into two tiers: the bottom tier represents static city entities, while the top tier captures dynamic aspects of city operations.

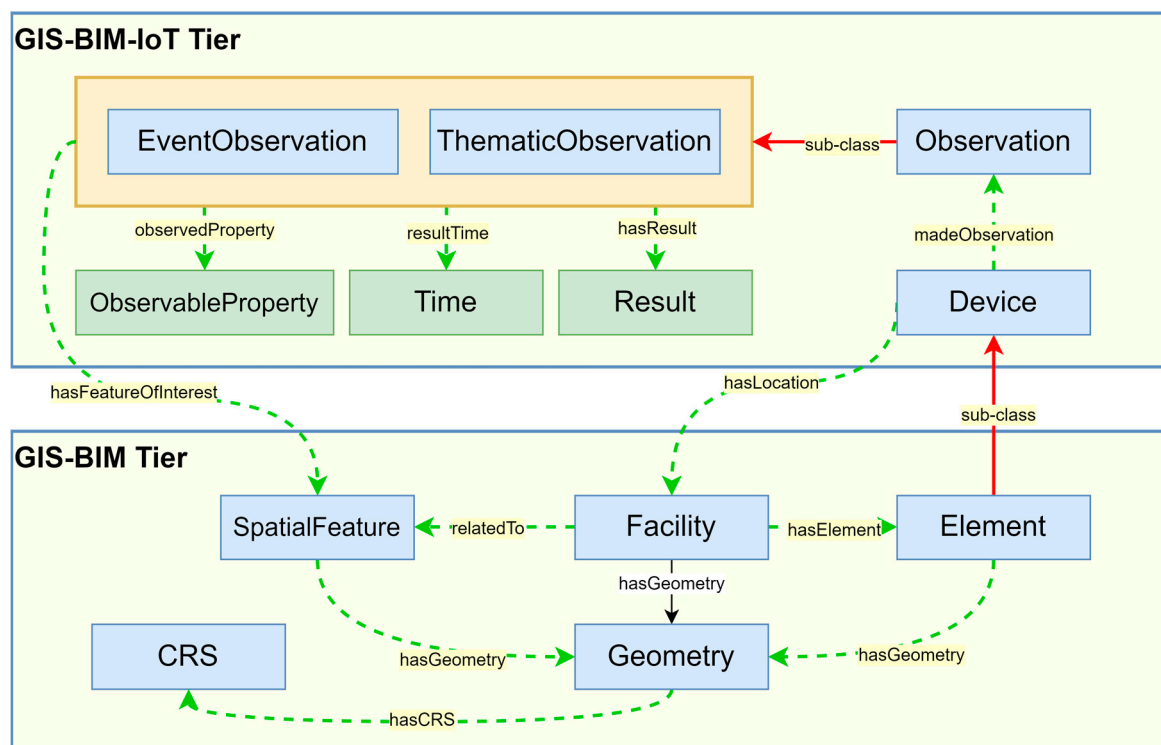


Figure 2. GIS-BIM-IoT integrated ontology (Green arrows represent object properties between different ontology classes. Red arrows denote class hierarchies (sub-class relationships)).

In spatial and built environment modeling, the ontology incorporates CityGML, IFCOWL, and GeoSPARQL. Building and asset semantics follow IFC and IFCOWL aligned with BOT. Sensors and observations follow SOSA and SSN, and Brick is used for equip-

ment classification when needed. Geospatial geometry, topology, spatial relations, and spatial joins follow GeoSPARQL. CityGML is used for city context geometry. Units are harmonized during data preparation and loading, and stable identifiers such as the IFC GlobalId are retained so that observations can be linked to assets and spaces through `sosa:hasFeatureOfInterest`. The ontology defines core classes including `esg:Geometry`, `esg:Facility`, `esg:Element`, `esg:SpatialFeature`, and `geosparql:CRS`. The integration of these classes and their relationships is illustrated in Figure 3, which shows GIS-related classes on the left (spatial features), BIM-related classes on the right (physical elements), and object properties in the right panel that define how these classes are linked. As an example, the class `esg:BuildingElement` is semantically mapped to `ifcowl:IfcBuildingElement`, demonstrating how ontology-level alignment ensures consistency across standards and ESG-specific extensions. Among these, `esg:Geometry` serves as the central class for spatial representation and is declared equivalent to `geosparql:Geometry`. It can be associated with GML types such as `gml:Point`, `gml:Curve`, `gml:Surface`, and `gml:Solid`, thereby supporting representations ranging from 2D footprints to full 3D volumetric forms. Geometric data are encoded using two formats: Well-Known Text (WKT), which provides a compact textual representation of geometric shapes (e.g., points, polygons, and volumes), and Geography Markup Language (GML), which offers a richer XML-based structure that includes both shape and associated coordinate reference system information. These are expressed in the ontology using `geosparql:asWKT` and `geosparql:asGML`, respectively, enabling flexible and standards-compliant representation of geometry for both GIS and BIM contexts. To reflect the varying levels of spatial detail required in ESG evaluation, the ontology introduces the data property `esg:lodType`, following CityGMLs level of detail (LoD) convention and dividing spatial resolution into five levels (LoD0–LoD4) as shown in Table 2. For instance, when assessing BIM delivery, LoD1 is adopted with a simple building block and its BIM submission status. In contrast, evaluating indicators like the recyclability of building materials requires LoD4 that captures detailed structural components such as walls, doors, and façade elements, enabling lifecycle tracking at the material level.

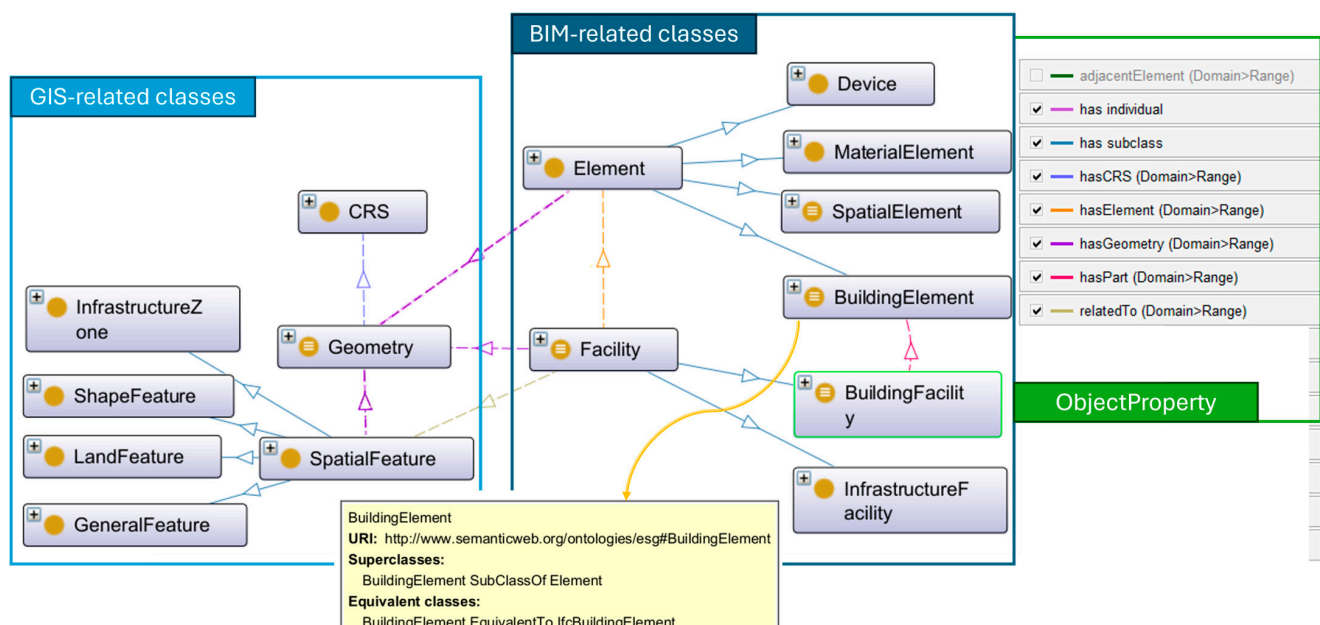


Figure 3. Ontology structure showing GIS- and BIM-related classes with key object properties (The URI shown in the figure, <http://www.semanticweb.org/ontologies/esg#BuildingElement>, was accessed on 17 September 2025).

Table 2. Geometric and semantic differences across LoD levels.

LoD Level	Representation Characteristics	Included Building Elements
LoD1	Simplified block model with flat roof	Building volume
LoD2	Adds roof details and external attachments such as balconies	Roof structures, balconies
LoD3	Complete exterior structure, including walls, roof, and possibly openings	Exterior walls, roof, and possibly doors/windows
LoD4	Includes internal structural components	Rooms, interior walls, stairs, furniture, etc.

For building component modeling, ontology adopts `esg:Element` as an abstraction of `IfcElement` in IFC, unifying the representation of building structures, spatial units, and sensor attachment points. Spatial topological relationships among elements are modeled via object properties such as `esg:hasPart/esg:isPartOf`, `esg:boundedBy/esg:bounds`, and `bot:adjacentElement`. The class `esg:Facility` represents physical entities with both structural and functional attributes, including residential buildings, commercial facilities, and civil infrastructure. Meanwhile, `esg:SpatialFeature` covers a broader set of spatial objects, such as administrative zones, land use units, and street boundaries, enabling integration with urban GIS layers. All spatial entities are linked to geometric representations through `esg:relatedTo`, forming a unified connection between semantic entities and spatial forms. The ontology also defines `esg:CRS` to standardize geodetic references across heterogeneous sources, supporting integrated spatial reasoning and alignment.

On top of the static spatial semantic structure, real-time monitoring of green city operations is enabled through IoT integration. The ontology incorporates the BRICK schema and W3Cs SSN/SOSA ontologies to formally represent sensors, observations, and measurement results. As shown in Figure 4, the core class `esg:Device`, defined as a subclass of `esg:Element`, is further divided into `esg:BuildingDevice` and `esg:InfrastructureDevice` to reflect the physical deployment of sensing equipment across buildings and infrastructure systems. According to ESG evaluation needs, specific subclasses such as `esg:Sensor`, `esg:Meter`, and `esg:Alarm` are defined to support the monitoring of key domains, including air quality, energy use, water and waste management, traffic flow, and ICT infrastructure, across both building-level and city-scale environments. While the BRICK ontology provides detailed modeling of building subsystems and sensor control logic, the present ontology extends these concepts to a broader urban context. Device locations are modeled using `brick:hasLocation`. Devices associated with buildings are linked to corresponding `esg:BuildingElement` instances, while those deployed in public infrastructure are linked to `esg:InfrastructureFacility`. For example, a smart water meter used to monitor treated water is located within an `esg:WaterUtilityFacility`.

All sensing activities are modeled as subclasses of `sosa:Observation`. These are organized into two branches: `esg:EventObservation`, which captures city-level events (e.g., service disruptions), and `esg:ThematicObservation`, which captures continuous or periodic measurements of key ESG indicators. `EventObservation` includes instances such as `esg:ICTOutageObservation`, which observes disruptions in ICT infrastructure. `ThematicObservation` includes domain-specific subclasses such as `esg:AirQualityObservation`, `esg:EnergyObservation`, `esg:WaterObservation`, `esg:WasteObservation`, `esg:TrafficObservation`, `esg:NoiseObservation`, `esg:ICTObservation`, and `esg:HousingObservation`, corresponding to measurable digital indicators used in ESG evaluations. Each observation instance contains semantic attributes such as the observed property (`sosa:observedProperty`), mea-

surement result (sosa:hasResult), timestamp (sosa:resultTime), and duration (esg:duration). Observations are linked to the responsible sensing device via sosa:madeBySensor and to the observed feature of interest, such as a specific building, room, public space, water body, or infrastructure facility, via sosa:hasFeatureOfInterest. Together, these links form a semantic bridge connecting physical urban entities with dynamic real-time sensing data streams.

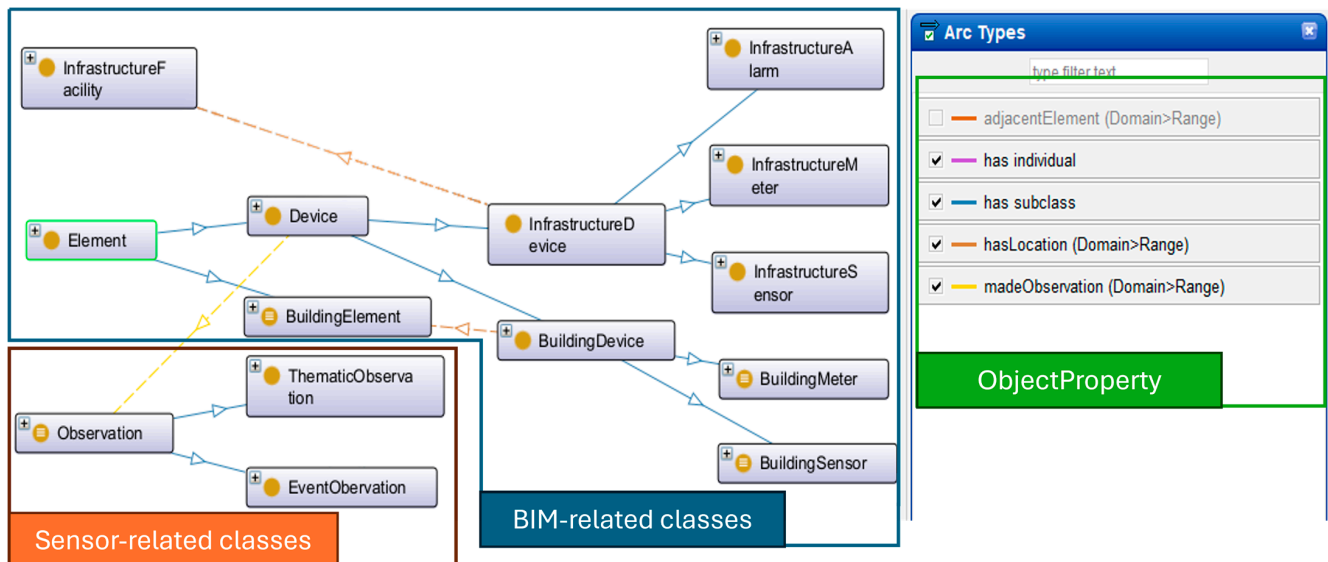


Figure 4. Ontology structure of ESG devices and observations.

3.2.2. Semantic Extension for ESG Evaluation

The foundational ontology alone cannot fully capture complex sustainability concepts required in ESG evaluation, particularly those involving regulatory compliance, operational status assessment, and historical traceability. For example, indicators such as “Percentage of buildings meeting thermal comfort standards,” “Transportation fatalities per 100,000 population,” and “Annual number of public transport trips per capita” involve abstract judgments and cross-modal information integration, which cannot be directly represented using only spatial or physical ontology structures. Therefore, this ontology introduces an ESG-oriented semantic extension layer atop the GIS-BIM-IoT framework. This layer incorporates specialized classes and properties to support unified data modeling and reasoning for ESG performance evaluation and intelligent decision-making in green cities.

From the perspective of integration capability and semantic abstraction, ESG indicators can be grouped into two categories. The first includes indicators that can be directly modeled using existing ontology structures—such as PM_{2.5} concentration; energy consumption; and per capita green space. These are typically represented via sosa:Observation, esg:Sensor, and sosa:Result, with support for spatial localization and LoD-based control. The second category includes governance-related concepts that require new semantic classes and properties, such as green certification, service interruption records, and BIM delivery status. To address these needs, new classes such as esg:Certificate and esg:Interruption, as well as key properties like esg:certificationLevel, esg:duration, and esg:type, are introduced to fill the semantic gaps in the existing model.

Based on the indicator content and modeling strategy, the ESG semantic extensions are structured into six thematic domains:

- **Environmental Quality**

Includes indicators such as PM_{2.5}, NO₂ concentration, air quality compliance rate, green space area, and green roof coverage. As shown in Figure 5, Pollutant concentrations are modeled using esg:AirQualityObservation, connected to specific pollu-

tants via `sosa:observedProperty`. Spatial indicators such as green areas and roofs are represented using subclasses of `esg:LandFeature`, with geometry defined via `geosparql:hasGeometry` and resolution specified by `esg:lodType`.

- **Energy and Built Environment**
Covers energy consumption in public buildings, share of renewable energy, green certifications, and BIM delivery. `esg:MaterialElement` is equipped with properties such as `esg:materialName` and `esg:materialWeight` to express material sustainability as shown in Figure 6. `esg:Certificate` records certification level, issuer, and date and is linked to specific `esg:Facility` instances. Renewable energy usage is annotated using the `esg:energySourceType` property.
- **Water and Waste Management**
Encompasses indicators like wastewater reuse rate, waste recycling rate, and drinking water compliance. Observations are represented by `esg:WaterObservation` and `esg:WasteObservation`, with results structured via `sosa:hasResult` and `esg:Result`, supporting alignment across time, location, and entity.
- **Mobility and Smart Transport**
Includes per capita public transport usage, non-motorized travel rates, smart traffic light deployment, and street lighting systems. Urban traffic infrastructure (e.g., smart street lights, signal systems) is modeled as semantic individuals via `esg:InfrastructureFacility` and described using attributes such as `esg:technologyLevel` and `esg:isRefurbished`.
- **ICT and Infrastructure**
Covers municipal internet coverage, real-time mapping systems, smart metering, and service interruption durations. `esg:InfrastructureZone` is used to represent the spatial scope of ICT deployments, while `esg:Facility` and `esg:Element` subclasses describe the density and distribution of smart devices. `esg:Interruption` class is used to model service disruptions, annotated with `esg:duration` and `esg:type` (e.g., ICT, water).
- **Housing and Social Inclusion**
Includes residential density, per capita living space, slum population ratios, and building comfort. Population attributes are assigned to `esg:AdministrativeArea`, while building comfort and acoustic performance are inferred through associated `esg:Certificate` levels, which reflect compliance with relevant well-being or green building standards.

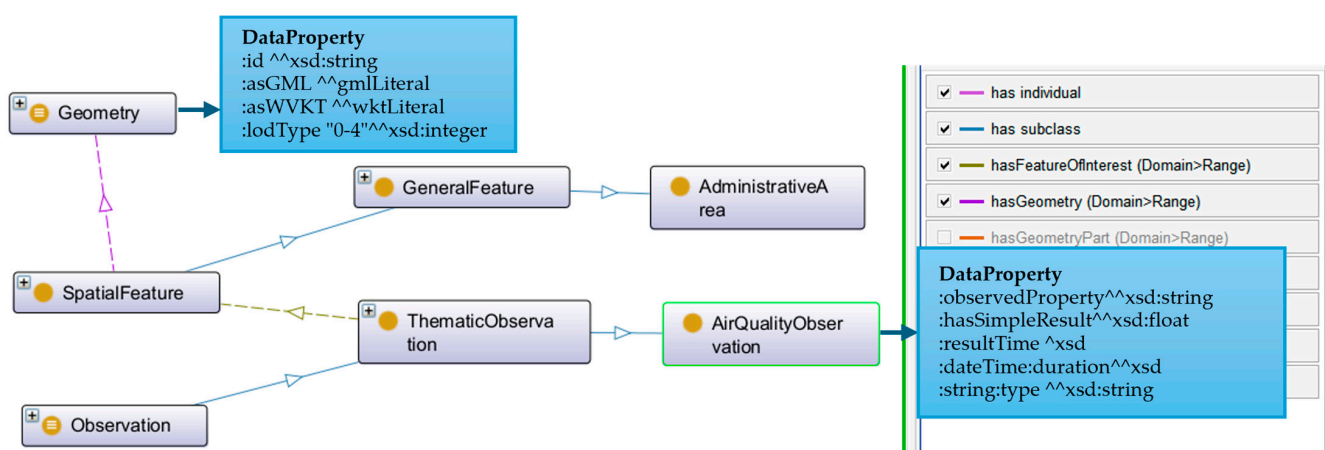


Figure 5. Ontology supporting pollutant concentration assessment in ESG evaluation.

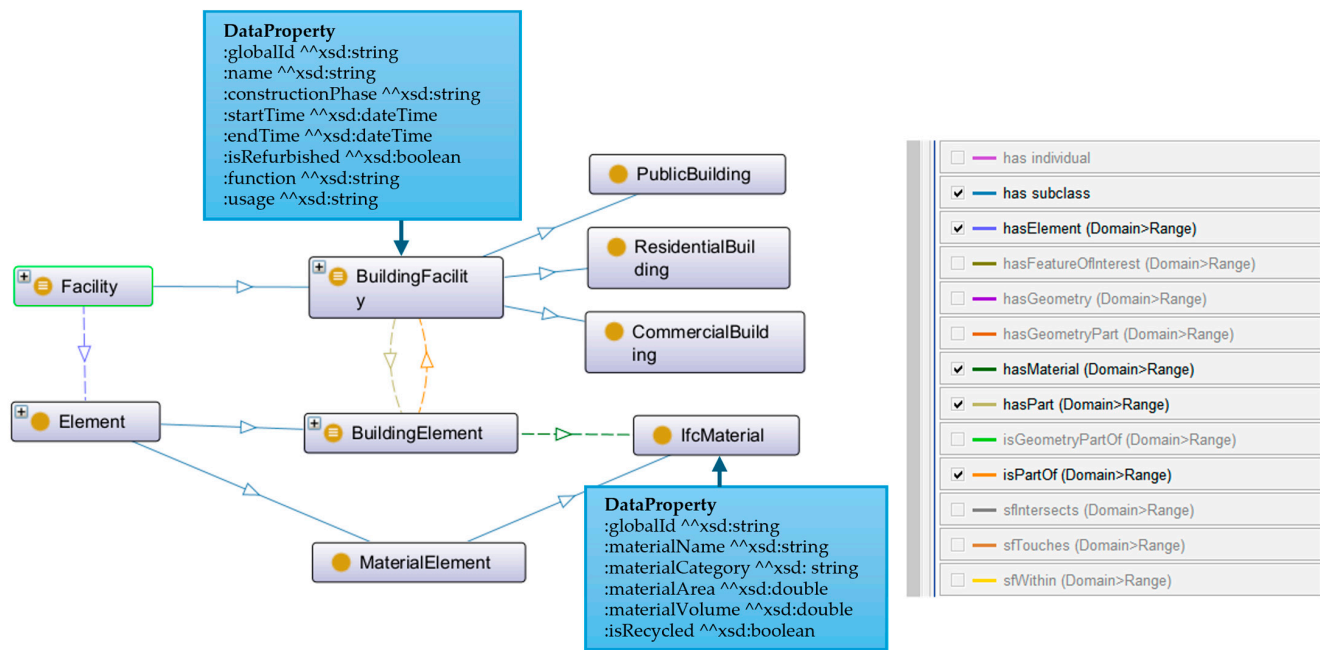


Figure 6. Ontology supporting reused building material assessment in ESG evaluation.

Through these six thematic domains, ontology significantly enhances the semantic expressiveness of ESG indicators and enables seamless linkage between physical space, real-time sensing data, and governance logic. This forms a robust knowledge graph foundation for future ESG reasoning, evaluation, and policy support.

3.2.3. ESG Indicator Reasoning

To enable automated computation and semantic evaluation of ESG indicators, this study introduces an RDF-based reasoning mechanism built upon the ontology framework. This mechanism follows a structured workflow involving rule definition, data transformation, graph loading, and rule execution, supporting scalable, explainable, and traceable evaluation of green city performance.

The process begins with the formalization of RDF reasoning rules tailored to specific ESG indicators. These rules are defined based on the classes and properties of the ontology and expressed using SPARQL CONSTRUCT queries, SHACL rule sets, or OWL reasoning profiles. The rules cover various logic types, such as quantity aggregation, conditional filtering, entity membership, and temporal constraints, allowing the derivation of indicator values from diverse sources, including sensor observations, building information, and governance records. To enable automated ESG indicator evaluation, this framework establishes a link between the nature of each data source, GIS, BIM, and IoT, and the types of sustainability attributes they are inherently suited to represent. GIS data, which captures the physical layout, zoning, and administrative structure of the city, provides essential context for indicators that are spatially distributed or population dependent. For example, indicators such as green space per capita, housing density, and access to mobility infrastructure depend not only on total quantities but also on their distribution across urban areas, which GIS systems can effectively express. BIM encodes detailed design, material, and performance-related information at the building or asset level. It offers a high-resolution foundation for evaluating construction-based indicators such as embodied carbon, material reuse ratio, and compliance with green building certifications. These indicators require access to material types, volumetric quantities, and spatial hierarchies, all of which are explicitly represented in IFC-based BIM models and can be semantically mapped through the ontology. IoT sensor data enables dynamic monitoring of urban conditions

and operational performance. Indicators such as air pollutant levels, energy consumption, noise pollution, and water usage are inherently time-sensitive and cannot be inferred from static sources. IoT observations provide the necessary temporal granularity to assess how real-world environmental conditions evolve and influence sustainability goals. By aligning data modalities with the conceptual semantics of ESG indicators, the framework ensures that each indicator is grounded in a logically consistent data source. Each indicator is then operationalized through semantic reasoning rules that extract, transform, and evaluate the relevant fields to generate normalized, explainable, and interoperable ESG scores.

Next, relevant data are extracted from heterogeneous raw sources. These sources may include BIM models (e.g., IFC files), urban GIS systems, IoT platforms, or statistical databases, containing information on building elements, material properties, spatial locations, device statuses, and sensor measurements. The extraction process focuses on identifying key fields, such as building IDs, component types, material volumes, and observation values, that are essential for semantic alignment. In the third step, the extracted data are transformed into RDF triples that comply with the ontology. This semantic transformation involves mapping data fields to corresponding ontology classes and properties using predefined rules or scripting functions. For example, a material and its attributes, such as volume and recyclability, are expressed as RDF individuals and literals, linked to their corresponding building components and facilities through semantic object properties.

Once transformed, all RDF triples are loaded into a reasoning-enabled knowledge graph, forming a unified semantic representation. This graph encodes both the core descriptions of entities and their cross-domain relationships, such as materials linked to components, devices to spatial locations, and sensors to facilities. On this basis, the predefined reasoning rules are executed to identify target entities, aggregate relevant properties, and compute ESG indicator values. Finally, the reasoning results are written back into the RDF graph using dedicated classes and properties such as `esg:ESGIndicator`, `esg:indicatorType`, `esg:indicatorValue`, and `esg:indicatorScore`. These results can then be consumed by visualization dashboards, time-series analysis tools, spatial comparison modules, or decision-support systems and can also serve as inputs to further reasoning or semantic queries.

Through this end-to-end workflow, from data acquisition and semantic modeling to rule execution and result publication, the system provides an intelligent and operable ESG evaluation framework for green cities.

3.3. Component 3: Implementation of GIS-BIM-Iot Data Integration

3.3.1. Overall Technical Framework

This component aims to establish a unified data integration layer that supports ESG-driven analytics and visualization by seamlessly combining spatial, semantic, and sensor data from diverse urban sources. This study adopts an integration approach based on web services combined with ontology semantic modeling to achieve the integration of GIS, BIM data, and real-time sensor information. This approach complements the technical layer and the semantic layer. At the technical level, the web-based integration approach has many advantages. First, it avoids the loss of semantic information and errors in geometry transformation caused by direct schema mapping between IFC and CityGML. Second, the schema-level GIS document provides a limited level of detail describing the geospatial environment. However, online GIS service usually provides an abundant source of data with real-time or periodic updating, including aerial maps, digital maps, and street-side 3D scenes. Additionally, GIS service uploads climate information from satellites, which is closely related to green building operation. Third, the web service is easier to connect with the cloud server of the equipped sensor. At the semantic level, as described in

Section 3.2, a GIS-BIM-IoT ontology was constructed as a semantic support for data fusion. The ontology formally defines the core concepts related to physical entities, dynamic IoT observations, and ESG evaluation. Ontology and web services are interconnected through identifier mapping and semantic annotations: real-time data streams from sensor APIs and GIS services are dynamically mapped to ontology instances, forming a consistent data graph with BIM and spatial data. Hence, based on this belief, the technical framework is developed as shown in Figure 7.

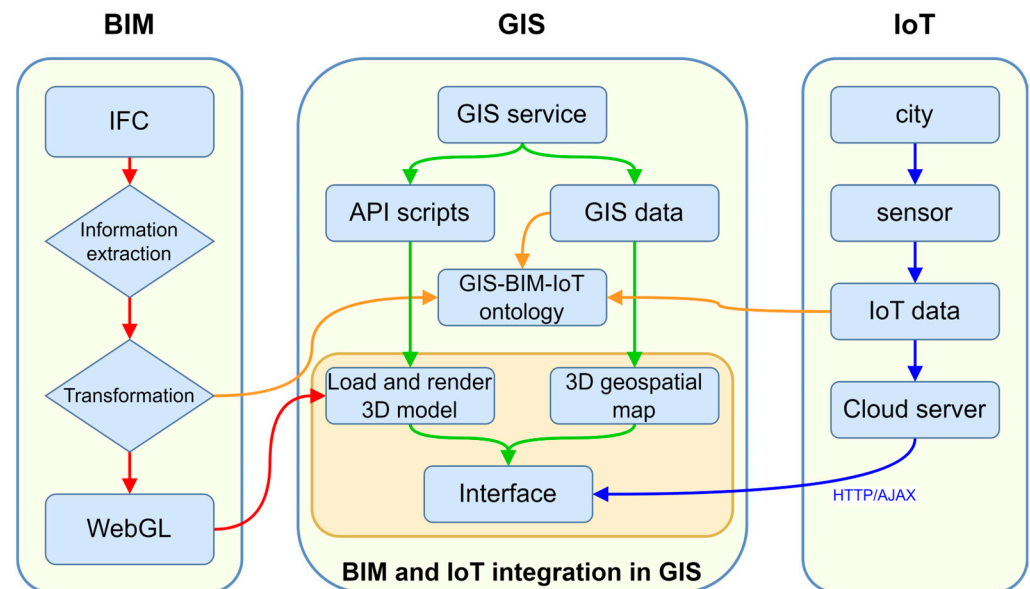


Figure 7. The overall technical framework of integrating GIS, BIM, and IoT data on GIS service (Red arrows represent the data flow from BIM-related sources; Green arrows indicate the flow of GIS-related data; Blue arrows show the flow of IoT data; and Orange arrows denote the integration flow across BIM, GIS, and IoT data) [50].

As presented in Figure 7, the framework constitutes three interrelated blocks: BIM, GIS, and IoT, which demonstrate how the data are collected, manipulated, and transferred.

- **BIM Block:** The IFC model is exploited as it is the most widely accepted standard in the AEC/FM industry [51]. The IFC model is firstly modeled in BIM software Rivet 2024, and it is processed by toolkits that can parse EXPRESS documents. The semantic and geometric information are extracted separately. Geometry information is transformed into WebGL. WebGL is a Web Graphics Library for rendering interactive 2D and 3D graphics in web browsers. The semantic information is organized in an independent document containing the demanding BIM family, project, and owner data.
- **IoT Block:** Multi-functional sensors are installed not only within buildings but also across the urban environment, including public infrastructure, transportation systems, and environmental monitoring stations. Their exact locations and functions are registered using ontology-based semantic models, which ensure consistent interpretation and alignment of sensor data across domains. These sensors detect parameters that can be used to evaluate the city's ESG performance and upload the streaming data to cloud servers.
- **GIS Block:** A GIS web service is employed that allows development upon it. Such service provides GIS data like globe maps as well as API scripts to allow developers to access and manipulate these data and build applications. Consequently, the GIS service could load the WebGL models representing the geometry of BIM with their real-world locations. Moreover, it also enables the sensors' cloud service via the HTTP/AJAX protocol and receives real-time data. Since each sensor is registered in

the BIM model, their global coordinates are also known after a set of transformations together with the BIM model. In a GIS environment, the geometry representation of a BIM model can be directly viewed, and sensor data can be visualized in different ways according to the purposes of green building operation and management. Apart from the geometry representation of BIM, semantic information is associated with its geometry in the GIS environment. Once a certain part of the BIM model is specified in the GIS environment, its linked semantic information would be retrieved and visualized via ontology-defined relations.

- BIM–GIS–IoT synchronization and scale: Sensor records are ingested at regular intervals as SOSA Observations with UTC timestamps and quality flags. Each record is linked to the corresponding building, room, public space, or area using persistent identifiers and spatial containment. Indicator values at a given time use the latest valid observation within a short lookback window. If no valid observation exists, the value is marked as missing. Static BIM and GIS layers are updated when authoritative models or base maps change. Indicator derivation is implemented with SPARQL rule and query logic in the triplestore, with lightweight OWL RL entailment for class and property closure and SHACL used for validation. Static relations such as type hierarchy, part–whole, and spatial containment are materialized in advance. Runtime queries use spatial indicators for GeoSPARQL. The current case study runs on one RDF graph store with a tiled web visualization front end. Performance is most affected by the volume of sensor records and by spatial joints over large areas. To keep latency low, data are ingested and queried in batches, and observations are pre-aggregated by time window and administrative unit prior to computing indicators.

3.3.2. Extraction, Transformation, and Reconnection of IFC BIM Model

As described in the previous section, the IFC model should be processed through several steps so as to be fused in a GIS environment. The procedure consists of information extraction, data transformation, and reconnection.

The information extraction step extracts geometry information and semantic information separately. It is ascribed to the fact that through the latter transformation, most of the semantic properties of the IFC model would be lost. To preserve such essential information, property information in the IFC model should be handled independently and generated as a single document in advance. Ontology-compliant RDF representations are adopted, taking advantage of their standardization, interoperability, and compatibility with semantic web tools. Hence, semantic properties extracted from the IFC model are formalized as RDF triples and instantiated within the GIS-BIM-IoT ontology. On the other hand, the geometry of the IFC model is extracted and converted to a pure 3D graphics model. The most commonly seen data types include OBJ, COLLADA, and FBX.

The transformation step converts the geometry of BIM into the ultimate 3D model, which is structured based on WebGL. Here, GLTF is chosen as the resulting representation of the geometry of BIM. GLTF is a royalty-free specification developed by Khronos Group for the efficient transmission and loading of 3D scenes and models based on WebGL [52]. It has several advantages pertaining to the scenarios of research: (1) It compresses the size of 3D content by isolating materials, hierarchy, geometry, and textures. Thus, the runtime processing on the browser could be efficiently minimized. (2) It has a node hierarchy network to present geometry units and their topology. Intuitively, it is suitable to reflect the topology information in the IFC model. Nonetheless, there is no direct way to convert IFC to GLTF. Existing toolkits and software allow the pipeline IFC–OBJ–GLTF or IFC–COLLADA–GLTF. After a GLTF model is generated, it is loaded by API scripts of the GIS web service. The necessary work that must be carried out is to transform the 3D model from its project

coordinate to its real-world global coordinate. The original coordinate could be multiplied by a translation and a rotation matrix to adjust its realistic location and orientation.

Having loaded the GLTF model in the GIS environment, the subsequent step is to link the RDF files containing the property information to the geometry model. To retain the identity of each BIM family in the GLTF geometry model, a small trick is played: at the beginning of the transformation step, loop every `IfcElement` in the IFC model and modify `IfcElement.Name = IfcElement.Name + "://" + IfcElement.GlobalId`. It counteracts the condition that the element ID in the IFC model could be eliminated during a set of transformations. After this manipulation, each geometry unit (node) in the final GLTF model would contain its original element name as well as its unified ID. For instance, a node in GLTF representing a door element could have a node name "Wood door:/322224". In reconnection, this node name can be easily decomposed using REGEX to acquire its family name and family GlobalID, respectively. GlobalID serves as a linking key to geometry and its corresponding semantic instance in the GIS-BIM-IoT ontology. Each geometry node is mapped to an `esg:Element` individual within the ontology, which captures key attributes such as `esg:hasMaterial`, `esg:boundedBy`, and `esg:isRecycled`, as well as dynamic links to sensor data using properties like `sosa:hasObservation`.

3.3.3. Sensor Data Collection and Transmission

A diverse range of urban sensors used to measure key parameters relevant to ESG evaluation are deployed across both indoor and outdoor environments, including buildings, infrastructure, and public spaces. These sensors monitor air quality, energy consumption, water usage, waste flow, noise levels, traffic conditions, environmental hazards, and the performance of ICT infrastructure. All sensors are registered as individuals in the GIS-BIM-IoT ontology and are annotated with properties such as `sosa:hasObservation` and `brick:hasLocation`. The sensor devices are connected via wireless networks (e.g., Wi-Fi, NB-IoT) and transmit real-time observation data to cloud servers maintained by government agencies or service providers. Within the GIS environment, asynchronous requests (e.g., via AJAX or HTTP-based APIs) are used to retrieve these data streams from the respective cloud endpoints. The ontology provides semantic mappings between each data stream and its corresponding observation, enabling dynamic integration into the knowledge graph. The collected data are visualized in the GIS interface using standard web technologies (HTML, CSS, and JavaScript) and are semantically enriched through ontology-based queries.

4. Case Study: Semantic Integration and ESG Indicator Inference Based on the Proposed GIS-BIM-IoT Ontology

To validate the feasibility and applicability of the proposed GIS-BIM-IoT ontology framework and its ESG indicator inference mechanism, two representative ESG indicators were selected for the case study: (1) the percentage of reused/recycled construction materials in new buildings, and (2) air pollution concentration, including typical pollutants such as $PM_{2.5}$, PM_{10} , and SO_2 . These cover complementary data-generating patterns, asset/design-driven (BIM-native) and observation-driven (IoT-native), thereby exercising the full pipeline. By extracting structured information from BIM models and IoT observations and transforming them into RDF representations, semantic integration and automated scoring of the two indicators were achieved through ontology-based reasoning and a unified scoring system. Because many indicators in Table 1 map to these two patterns, the workflow generalizes with minimal extensions.

4.1. Semantic Modeling and Inference of the Recycled Construction Material Indicator

A primary school in Hong Kong was selected as the target building. The architectural model was created using Autodesk Revit, focusing on architectural discipline, with a Level of Development (LoD) between 300 and 400. The model includes accurate geometric and material information for the building envelope and furniture systems.

Figure 8 illustrates the full semantic workflow for computing the ESG indicator material RecycleRatio based on BIM data. The Revit model was exported to the IFC format and parsed using the open-source Python library ifcopenshell, which provides efficient access to IfcBuildingElement, IfcMaterial, and associated geometric attributes. Scripts were used to extract all component types, volumes, material names, and material relationships. The extracted data were then transformed into RDF triples and mapped to the proposed ESG ontology. During modeling, each building element was represented as an instance of `esg:BuildingElement`, and associated materials were represented as instances of `ifcowl:IfcMaterial`, linked via the object property `esg:hasMaterial`. The component volume was recorded using `esg:volume`, while the area and volume of each material were calculated by aggregating all instances of that material used across the entire building and were assigned using `esg:materialArea` and `esg:materialVolume`. These aggregate computations relied on ifcopenshell's geometric interfaces and the hierarchical relationships between elements and materials.

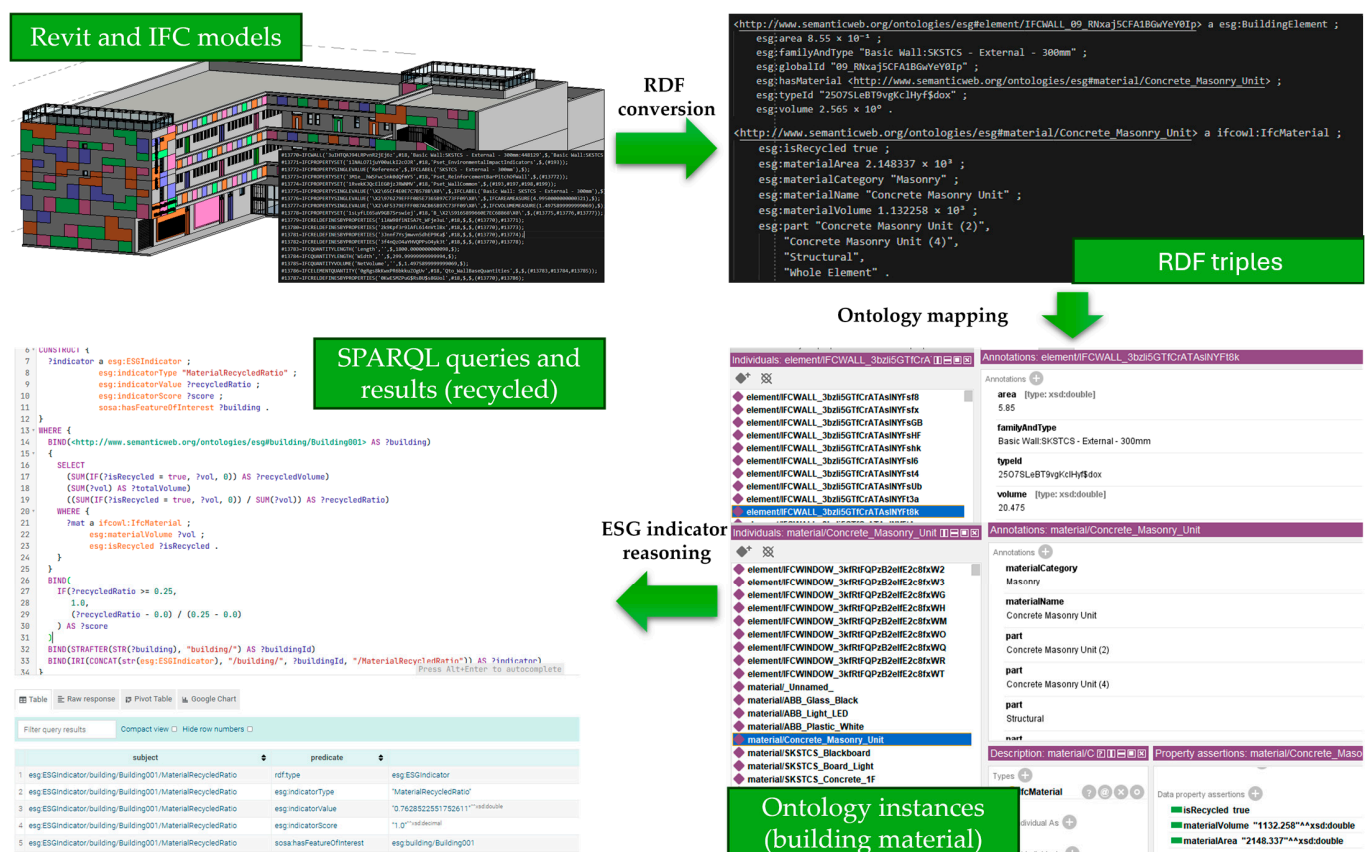


Figure 8. Semantic inference workflow for calculating the material recycling ratio from BIM using IFC parsing, RDF transformation, ontology instantiation, and SPARQL-based ESG indicator computation.

To simulate the identification of recyclable materials, the material Concrete Masonry Unit was defined as recyclable by adding the Boolean property `esg:isRecycled = true` to its semantic individual. The resulting semantic knowledge graph was loaded into the GraphDB database and subjected to semantic reasoning using SPARQL rules to automatically compute the proportion of recycled materials to the total material volume.

The inference result was encapsulated in an instance of `esg:ESGIndicator`, a core indicator structure pre-defined in the ontology to uniformly represent all ESG-related data as RDF triples. Each instance of `esg:ESGIndicator` includes the following key properties:

- `esg:indicatorType`: the type of indicator (e.g., `esg:materialRecycleRatio`);
- `esg:indicatorValue`: the inferred raw value;
- `esg:indicatorScore`: the normalized score computed under the unified scoring system.

In this case, the inference result indicated that the total volume of recycled materials was 1132.258 m^3 , and the total material volume was 1484.243 m^3 , resulting in a material recycle ratio of 0.763. This value was recorded as `esg:indicatorValue` in the semantic graph.

The value was subsequently normalized according to the unified ESG scoring mechanism introduced in Section 3.1. This mechanism supports both positive and negative indicators and allows configuration of upper and lower bounds, segmentation, and saturation logic. As a positive indicator, the predefined scoring range was $[0, 0.25]$. Since the actual value exceeded the upper bound, the system assigned the maximum score of `esg:indicatorScore` = 1.0 based on the saturation rule, indicating outstanding performance in material recyclability. The entire indicator structure, including type, value, and score, was stored in the knowledge graph in the form of structured RDF triples, enabling structured querying and seamless integration into the visualization platform.

4.2. Dynamic Inference and Scoring of the Air Pollution Concentration Indicator

The second validated indicator focused on air pollution concentration. A real-world air quality monitoring station located in Tseung Kwan O, Hong Kong, was selected for modeling, semantic positioning, real-time data integration, and scoring inference as shown in Figure 9. This process covered the semantic fusion of static BIM information with dynamic IoT observation data, supporting continuous updates and incremental writing into the RDF graph.

The monitoring station model was built using Revit, and semantic properties were added to support spatial modeling. The sensor's location within the facility was expressed using `brick:hasLocation` and `bot:hasSpace`, while the facility itself was linked to the administrative region of Tseung Kwan O through `esg:relatedTo`. The geometry of the facility was connected using `esg:hasGeometry` and its coordinates recorded using `geo:asWKT`. These static triples defined the spatial and administrative boundaries for referencing dynamic observations.

Real-time air quality data were obtained through the World Air Quality Index (WAQI) platform, with a scheduled script updating the data daily. The acquired data were parsed and semantically modeled as instances of `esg:AirQualityObservation`, linked to sensors using `sosa:madeObservation`. Each observation included a timestamp (`sosa:resultTime`) and observation result (`sosa:hasResult`) and was linked to the monitored region using `esg:hasFeatureOfInterest`. Since air pollution involves multiple pollutant types (e.g., $\text{PM}_{2.5}$, PM_{10} , SO_2), each observation was further refined using `sosa:observedProperty` to specify the pollutant type and `sosa:hasSimpleResult` to record the concentration value.

The static semantic graph and dynamic IoT observations were integrated in GraphDB. The system extracted the latest observed values via SPARQL queries and automatically constructed corresponding `esg:ESGIndicator` instances for each pollutant. Each pollutant-specific indicator followed the same structure with three properties: `esg:indicatorType`, `esg:indicatorValue`, and `esg:indicatorScore`.

As a negative indicator, the air pollution score was normalized based on the unified ESG scoring mechanism described in Section 3.1. Taking PM_{10} as an example, its `indicatorType` was set as “ PM_{10} concentration” with an annual mean unit of $\mu\text{g}/\text{m}^3$. The observed value (`indicatorValue`) was 35, falling within the predefined scoring range of $[15, 70]$. Using

a linear reverse normalization function—where higher values yield lower scores—the system computed the final indicatorScore as 0.64; indicating moderate pollution pressure despite not exceeding the standard threshold.

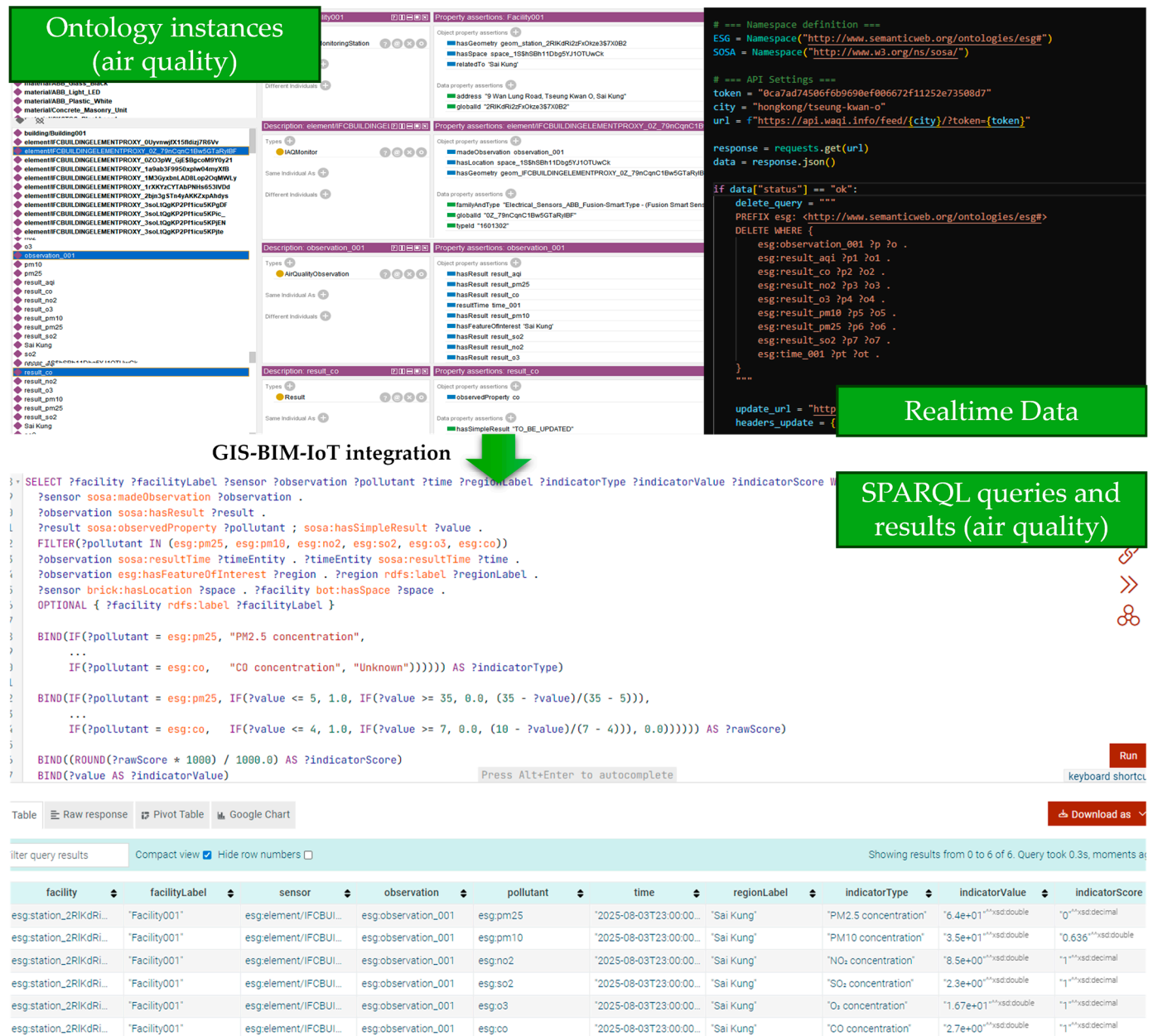


Figure 9. Semantic integration and reasoning workflow for air pollution concentration indicators using real-time data, ontology-based modeling, and SPARQL-based ESG scoring.

The full indicator result was written to the RDF graph as:

- `esg:indicatorType = "PM10 concentration"`
- `esg:indicatorValue = 35`
- `esg:indicatorScore = 0.64`

All indicator results were represented as RDF triples, enabling automatic updates as API data changed and maintaining real-time synchronization with the environmental state of the city.

4.3. Integration into a Web-Based 3D Visualization Platform Using Cesium

Based on the above modeling and inference processes, the BIM models, semantic knowledge graphs, and ESG indicator results were integrated into a unified web-based 3D visualization platform. To ensure compatibility with GIS rendering engines, the Revit models were first converted to glTF format and loaded into Cesium. Cesium, as an open-source WebGL-based geospatial visualization engine, supports multi-source data fusion and real-time rendering, enabling efficient spatial expression of buildings, facilities, and indicator results [53].

Within the platform as shown in Figure 10, the target building (e.g., the primary school) and surrounding facilities (e.g., the air quality monitoring station) are visualized. ESG indicator scores extracted from the semantic graph are dynamically rendered. The interface displays overall ESG performance along three dimensions—Environment; Social; and Governance—along with the composite ESG score; enabling high-level evaluation by city policymakers. An indicator panel presents a dropdown list where each `esg:ESGIndicator` can be explored individually, showing its `indicatorType`, `indicatorValue`, and `indicatorScore` to support fine-grained strategic analysis.



Figure 10. Web-based 3D visualization platform displaying ESG indicator results, building semantics, and environmental sensor integration in Cesium (The purple boxes highlight the total ESG score and its sub-scores and the orange boxes highlight detailed information for individual ESG indicators).

In addition, a component-level panel on the right side of the interface enables querying of building components based on semantic information. By clicking any building element, users can view its `familyAndType`, `typeId`, `volume`, whether it is made of recyclable materials, the material composition, and its contribution to the material recycling indicator, thereby enabling multi-scale interaction from city to building to component.

This case study validates the feasibility of an ESG evaluation system based on semantic modeling and a unified indicator structure within the context of green city governance. Through the complete modeling, semantic integration, automated scoring, and platform-level visualization of two key indicators—material recycling rate and air pollution concentration—the framework demonstrates strong potential for enabling transparent; logically consistent; and automatically updatable ESG management in urban environments.

5. Discussion

5.1. Implications and Contributions

This study advances ESG-driven urban evaluation by implementing a scalable and interoperable GIS–BIM–IoT integration framework supported by a unified semantic ontology. At the research level, it makes two key contributions: (1) It reconceptualizes ESG evaluation as a real-time, semantically grounded governance mechanism and proposes a methodology for automated ESG inference through ontology-based integration of spatial, building, and sensor data; and (2) it promotes the standardization of cross-scale ESG assessment by integrating GIS, BIM, and IoT data into a unified RDF-based ontology that ensures consistent operation across city, district, building, and component levels. The following discussion outlines the key practical implications of the proposed framework:

Unlike widely used ESG frameworks such as ISO 37120 [10] and CPI [11], which provide detailed conceptual definitions and suggested data sources, these standards do not prescribe technical mechanisms for real-time data collection. Moreover, unlike previous digital twin-based ESG studies [18–20] that focus on isolated domains or rely on static, post-hoc data, the proposed model introduces a proactive data capture pipeline that explicitly defines data flows and indicator logic at the design stage. While several commercial ESG dashboards, such as GRESB [54] and LSEG Data & Analytics [55], incorporate elements of automated data acquisition, they typically lack the ability to compute ESG scores directly from semantically integrated data sources. In contrast, the presented framework enables structured RDF representation, rule-driven indicator computation, and immediate spatial contextualization through a unified semantic ontology. Compared to conventional city-level ESG assessments that often depend on PDF reports or disconnected spreadsheets, this approach enhances scalability, interoperability, and the granularity of insight, enabling more consistent, transparent, and actionable ESG evaluation.

Existing literature often overlooks the reasons why fully integrated ESG digital twins remain underdeveloped. Two key barriers can be identified. First is the lack of stable identifiers and consistent ontologies to bridge domain-specific data. Second is the absence of standard data governance models that support semantic enrichment and continuous updating. These challenges are addressed through alignment with established standards such as IFC, BOT, SSN/SOSA, and GeoSPARQL, and through the use of persistent GlobalIds and linked semantic relationships across asset, observation, and spatial layers.

In contrast with existing smart city platforms like Autodesk Tandem [56] and Bentley iTwin [57], the proposed framework explicitly targets ESG-specific requirements. Most of these tools focus on geometric or operational data exchange but do not formally define ESG indicators, nor do they provide reasoning capabilities or semantic linkage between ESG concepts and physical elements. In the proposed framework, both the data acquisition plan and ontology design are directly informed by ESG evaluation requirements, ensuring that all collected data can be semantically aligned and computationally actionable for indicator derivation.

Multi-scale visualization capabilities are implemented through a Cesium-based 3D web interface that links ESG indicators to physical urban elements. Users are able to drill down from districts to buildings and components and inspect underlying evidence through interactive interfaces. Compared with static dashboards or tabular scorecards, this visual representation provides a more intuitive understanding of ESG drivers and supports actionable insights for planners and decision-makers.

ESG scores are not computed as opaque aggregates. They are derived through traceable SPARQL rule logic, with each value linked to specific assets or sensors. This creates a transparent chain from raw input to normalized indicator values. The approach enhances trust, auditability, and explainability, which are frequently absent in traditional ESG reporting systems.

5.2. Limitations and Future Work

Manual Modeling Steps: The current pipeline involves manual instantiation of ontology classes, rule definition, and data mapping, which can limit deployment speed and scalability. Future work will incorporate AI-based tagging, automated semantic mapping, and low-code rule editors to reduce expert workload.

Limited Governance Coverage: Governance indicators such as permitting efficiency, open data availability, and green spending share were underrepresented due to the lack of accessible machine-readable government data. Future work will extend the ontology to support administrative processes and institutional datasets and pilot the integration of government APIs or procurement logs where available.

Limited Scope of Case Study: The current validation involves only one building and one monitoring station, selected to test the end-to-end feasibility of the ESG evaluation pipeline. This narrow scope limits the demonstration of scalability across diverse urban contexts. Future work will extend the framework to incorporate multiple ESG indicators and asset types and test its performance in more complex, multi-source city environments.

Dependence on Data Quality and Availability: The system's performance relies on the completeness and interoperability of BIM, GIS, and sensor data, which varies significantly across cities. To address this, future iterations will embed missing data estimation methods (e.g., spatial interpolation, knowledge graph completion) and propose a data readiness assessment module to guide pre-deployment validation.

Visualization and Interaction Enhancements: Currently, the interface supports multi-scale 3D navigation and indicator lookup, but it lacks advanced user interactions such as what-if scenario panels, hotspot ranking, or AI-driven suggestions. These features are being planned for future iterations to enhance usability for strategic urban decision-making.

6. Conclusions

Urban ESG evaluation remains challenged by fragmented data sources and retrospective reporting mechanisms that hinder timely and actionable sustainability governance. Prior efforts often lack semantic consistency and fail to integrate spatial, infrastructural, and sensor-based data within a unified framework. This study introduces a standards-based ESG evaluation pipeline that semantically integrates GIS, BIM, and IoT data using a unified ontology aligned with IFC, BOT, SSN/SOSA, and GeoSPARQL. ESG indicators are formalized through ontology-linked rules and computed automatically using SPARQL queries. The framework supports real-time data ingestion, spatial reasoning, and indicator derivation across environmental, social, and governance dimensions. All outputs are visualized within an interactive 3D platform that enables multi-scale navigation and evidence-based exploration of ESG scores. A case study involving a school building and a local air quality sensor demonstrates the system's feasibility for dynamic indicator generation, semantic linking of observations to assets, and intuitive 3D visualization.

This work advances ESG evaluation from static documentation to a proactive, semantically grounded decision-support system. It improves the scalability, traceability, and granularity of urban ESG assessments and provides a transparent logic for deriving indicators from structured data. The integration of spatial and observational layers further enhances interoperability and contextual insight. Nonetheless, limitations remain. Some processes, such as ontology population and rule definition, still require manual input. Indicator thresholds are currently derived from literature benchmarks, which may not fully reflect local or evolving conditions. Future work will focus on automating these components using AI-based knowledge extraction and aligning thresholds through continuous, multi-city data integration to improve adaptability and robustness.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Initial Selection of ESG Indicators with Respective Sources

Environment		Sources (Union)
Air Quality	Fine particulate matter (PM2.5) concentration	BREEAM
	PM10 concentration	BREEAM
	NO2 concentration	BREEAM
	SO2 concentration	BREEAM
	O3 concentration	BREEAM
	Number of days with unhealthy air quality	BREEAM
	Number of real-time ICT-based air quality monitoring stations per 100 000 population	Customized
	Compliance rate of air quality	Customized
Climate & Energy	Greenhouse gas emissions measured in tonnes per capita	BREEAM
	Percentage of total energy derived from renewable sources	BREEAM
	Energy consumption of public buildings per year	BREEAM
	Total residential electrical energy use per capita	BREEAM
	Total electrical energy use per capita	BREEAM
	Energy from wastewater per capita	BREEAM
	Energy from solid waste per capita	BREEAM
	Percentage of energy from decentralized production systems	BREEAM
	Storage capacity of the energy grid per capita	BREEAM
	Energy consumption of public street lighting	BREEAM
Green Infrastructure	Percentage of street lighting refurbished	BREEAM
	Percentage of building energy from renewable sources	BREEAM
	Green area (hectares) per 100 000 population	BREEAM
	Annual number of trees planted per 100 000 population	BREEAM
	Kilometres of bicycle paths and lanes per 100 000 population	BREEAM
	Buildings built/refurbished in last 5 years conforming with green building principles	BREEAM
	Percentage of public buildings requiring renovation/refurbishment (by floor area)	BREEAM
Bio & Env	Percentage of buildings with green roofs	BREEAM
	Percentage of public landscape area with permeable or natural materials	BREEAM
	Hazardous Waste Generation per capita (tonnes)	BREEAM
	Percentage change in number of native species	BREEAM
Waste & Water	Annual frequency of ecosystem remote sensing monitoring	BREEAM
	Percentage of the city's solid waste that is recycled	BREEAM
	Percentage of treated wastewater being reused	BREEAM
	Percentage of city population with sustainable access to an improved water source	BREEAM
	Annual hours of water service interruption per site	BREEAM
	Percentage with telemetering-equipped waste drop-off centres	BREEAM
	Percentage with door-to-door garbage collection + telemetering	BREEAM
	Percentage of real-time environmental water quality monitoring stations per 100 000 population	BREEAM
	Percentage of reused/recycled construction materials in new buildings	BREEAM
	Percentage of drinking water under real-time quality monitoring	BREEAM
	Compliance rate of wastewater treatment	BREEAM
	Compliance rate of water quality	BREEAM

Figure A1. Cont.



Figure A1. Cont.



Figure A1. Initial selection of ESG indicators with respective sources.

Appendix B. The Fundamental Scale of Absolute Numbers

Table A1. The fundamental scale of absolute numbers.

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
Reciprocals of above	If activity i has one of the above nonzero numbers assigned to it when compared with activity j , then j has the reciprocal value when compared with i	
Rationals	Ratios arising from the scale	A reasonable assumption
		If consistency were to be forced by obtaining n numerical values to span the matrix

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