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Landscape to Digital Twins: A Geospatial Framework for the Development of Energy Digital Twins (EDTs) for Sustainable Urban Built Environments

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Abstract of the research

Over the last decade, recent advances in geospatial technologies have enabled more detailed modelling of urban built environments through Urban Digital Twins (UDTs). Urban Digital Twins (UDTs) are dynamic data-driven digital representations of urban environments that integrate spatial, temporal, and semantic information to support analysis, simulation, and decision-making processes. The research focuses on a framework for the development of Energy Digital Twins (EDTs), a specific UDT application that models energy behaviour to enhance urban energy efficiency. EDTs uses geospatial datasets to incorporate 3D city models to integrate and dynamically update energy metrics within the built environment. This work integrates data from advanced geospatial techniques and energy metrics into 3D WebGIS platforms and provides a conceptual framework for EDTs development from the geospatial datasets. This framework provides a practical, operational, data-driven approach to urban energy planning and supports sustainable city development.

This doctoral research centres on the continuous efforts to establish a conceptual framework for developing an Energy Digital Twin (EDT) for the urban environments employing geospatial datasets to extract actionable insights for a smart energy management system. This research develops operational procedures for energy modeling within Energy Digital Twins (EDTs), specifically the extraction of window and rooftop attributes from point cloud datasets. To address the practical problems of developing urban EDTs, the study evaluates computer vision techniques for building feature extraction and studies the impact of the resolution of the dataset on the accuracy of the required building features extraction from the geospatial datasets.

The main scientific contribution of this work is a comprehensive workflow to develop an Energy Digital Twin (EDT) from geospatial datasets. The methodology in this research explores the key building features necessary for the development of EDT and the way they can be derived from the geospatial datasets to build the base of an EDT. This research integrates geometric reconstruction, computer vision, and energy simulation into a framework for urban-scale energy analysis. The study evaluates how data resolution and feature sensitivity impact model reliability, establishing a technical foundation for the development of Energy Digital Twin (EDT) systems.

The major outcome of this PhD research is a complete framework for the development of an EDT environment for the urban environments. This research provides cities with a functional framework to visualise current energy scenarios and to assess the impact of future urban developments. Commercial solutions for the development of EDTs exist, but they are often not accessible to local governance; this work bridges this gap for developing a user-friendly platform specifically tailored to municipal decision-making. The study provides a data-driven, practical framework for authorities to implement and monitor urban sustainability policies, by facilitating the integration of 3D geometry and energy metrics.

Keywords: Urban Digital Twins (UDTs), Energy Digital Twins (EDTs), photogrammetry, point clouds, smart energy systems, urban environments, feature extraction, energy modelling, solar energy, sustainability.

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“ You will always go farther than what you think. ”

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Abbreviations

AI	Artificial Intelligence
AR	Augmented Reality
BEM	Building Energy Model
BEMS	Building Energy Management Systems
BIM	Building Information Models
BMS	Building Management Systems
CAD	Computer-Aided Design
CityGML	City Geography Markup Language
CRS	Coordinate Reference System
DEM	Digital Elevation Model
DL	Deep Learning
DT	Digital Twins
EDT	Energy Digital Twins
EO	Earth Observation
EPC	Energy Performance Certificate
GHG	Greenhouse Gas
GIS	Geographic Information Systems
GNSS	Global Navigation Satellite Systems
HVAC	Heating, Ventilation and Air Conditioning
IFC	Industry Foundation Classes
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IoT	Internet of Things
JSON	JavaScript Object Notation
LiDAR	Light Detection and Ranging

LOD	Level of Detail
ML	Machine Learning
MMS	Mobile Mapping System
OGC	Open Geospatial Consortium
PV	Photovoltaic Potential
RMSE	Root Mean Square Error
SDG	Sustainable Development Goal
SDT	Spatial Digital Twins
SEMS	Smart Energy Management Systems
SHGC	Solar Heat Gain Coefficient
SQL	Structured Query Language
UAV	Unmanned Aerial Vehicle
UDT	Urban Digital Twins
UTM	Universal Transverse Mercator
VR	Virtual Reality
WFS	Web Feature Service
WMS	Web Map Service
XML	Extensible Markup Language

Chapter 1

Introduction to research topic

The global energy sector is undergoing a critical transition driven by rapid urbanization, increasing energy demand, and the escalating impacts of climate change. Urban areas have emerged as dominant consumers of energy, accounting for nearly 70–80% of global energy use and greenhouse gas (GHG) emissions (Verma et al., 2021). This concentration of energy demand within cities places the urban built environment at the centre of sustainability challenges. Buildings, infrastructure, and urban systems not only influence energy consumption patterns but also affect environmental efficacy, human comfort, and enduring urban resilience (Bera & Nag, 2025; Shi et al., 2025). Improving energy efficiency in urban areas is key to sustainable development and reducing the environmental footprint.

Designing, managing and operating the urban built environment requires a detailed understanding of different elements and flows across multiple spatial and temporal dimensions (Bao et al., 2023; Sáenz de Tejada et al., 2024). Conventional methods for energy assessment are typically based on static models or limited data, and do not reflect well the complexity and dynamics of urban systems (Koirala et al., 2025). As urban areas develop, there is an increasing demand for advanced approaches that can more precisely depict real-world conditions, facilitate ongoing monitoring, and allow for predictive analysis (Cina et al., 2025; Son et al., 2023). These strategies are essential for optimising energy use, minimising inefficiencies, and facilitating informed decision-making for

planners, engineers, and policymakers for an efficient and sustainable planning of cities.

The most recent advances in geomatics and geospatial technologies present novel opportunities to tackle these difficulties for sustainable built environments. The geospatial datasets, sourced from remote sensing, geographic information systems (GIS), and three-dimensional urban models, offer comprehensive spatial information regarding metropolitan morphology, land utilisation, architectural attributes, and environmental conditions (Jamil, 2025; Labetski et al., 2023; Peldon et al., 2024a). These datasets are useful to provide a comprehensive understanding of the impact of urban topography on different building metrics like energy efficiency possibilities, building health, construction and structural distribution (Y. Li & Feng, 2025a; Sisman et al., 2025; P. Zhang et al., 2023). In urban areas with high energy consumption, the incorporation of geospatial data into energy analytic frameworks can facilitate the formulation of targeted initiatives to mitigate carbon emissions and enhance energy efficiency (Y. Li & Feng, 2025a; Rahmati et al., 2024).

The concept of "Digital Twins" represents the decade-long transition from real urban landscapes to data-driven digital representations. A digital twin is a dynamic, virtual replica of a real-world system that is constantly updated with data from many sources (Hananto et al., 2024; ISO/TC 211, 2020; Saeed et al., 2022). When applied to energy systems, Energy Digital Twins (EDTs) create a framework for modelling, monitoring, and optimising energy performance in the urban built environment (H. Li & Hong, 2025). EDTs enable the representation of buildings and urban systems not only in terms of physical attributes, but also in terms of energy behaviour, by combining geospatial datasets with energy modelling tools (Cespedes-Cubides & Jradi, 2024). This integration enables real-time analysis, scenario testing, and predictive modelling, which are essential for sustainable energy management.

Despite the potential of geospatial data and digital twin technologies, developing integrated, data-driven frameworks for urban energy management is a continuous problem (Abdessadak et al., 2025; H. Liu et al., 2023; Omrany et al., 2025). Existing techniques and framework for frequently lack interoperability between datasets, have difficulties in identifying the necessary building elements accurately, and are limited to capture the multi-scale nature of urban systems, or do not fully capitalise on the spatial dimension of energy processes (Alhammad et al., 2024; Castellanos et al., 2025; Quek et al., 2023). Furthermore, the

heterogeneity of urban data sources, as well as the complexity of energy systems, need the use of resilient computational methods that can handle huge volumes of data while preserving accuracy and reliability (Buonomano et al., 2026; Dritsas & Trigka, 2025; Keirstead et al., 2012). Addressing these issues is critical for developing the use of digital twins in the energy sector, and it is the fundamental goal for this doctoral research.

Geospatial datasets are crucial in this context, offering spatially explicit information that facilitates the investigation of energy consumption trends, urban morphology, and renewable energy potential. Building geometry, orientation, and material characteristics impact heating and cooling requirements, whereas urban density and land use patterns influence energy distribution and infrastructure development (Mahmoud, 2022; Najjar et al., 2025). Along with that, it is possible to combine spatial data with environmental variables such as solar radiation, temperature, and wind conditions to analyse the potential of integrating renewable energy in urban zones (Ramirez Camargo & Stoeglehner, 2018; Sakti et al., 2023). The possibility of aggregating these heterogeneous metrics into one framework leads to a better understanding of urban energy systems.

The integration of geographical data with energy performance metrics facilitates the development of systems competent at monitoring and forecasting energy behaviour in near real-time (Ahmad Hamdan et al., 2024; Kochanek et al., 2025). These capabilities correspond with global sustainability goals, including Sustainable Development Goal (SDG) 7, which emphasises access to affordable, dependable, sustainable resources of energy, and SDG 11, which seeks to create inclusive, safe, resilient, and sustainable cities (Blasi et al., 2022; Sharifi et al., 2024; United Nations, 2023). Geospatially enabled digital twins enhance energy efficiency and facilitate the integration of renewable energy sources, so directly contributing to these objectives.

Sustainable Energy Management Systems (SEMS) utilise advanced computational methodologies, geospatial technology and energy modelling techniques as a way to enhance energy consumption, distribution and generation in urban environments (O'Dwyer et al., 2020; Rao et al., 2025; Sola et al., 2020). The incorporation of digital twin concepts into SEMS enhances their functionality by allowing a continuous flow of data between the physical system and its digital twin. Such integration allows for adaptive management tactics, better scenario-based analysis, and overall efficiency and resilience of urban energy systems. The aim of this doctoral research is to develop a conceptual geospatial framework

for the generation of Energy Digital Twins, to bridge the gap between the real landscape and digital representations of urban energy systems. The objective of this research is to develop a conceptual framework for a data-driven and scalable approach to evaluate and optimise the energy performance in urban built environments. This is intended to be accomplished by merging multi-source geospatial datasets with the most advanced energy modelling techniques currently available. The undertaken research aims to address present limits in data integration, geographical modelling, and real-time analysis, thereby advancing digital twin applications for sustainable urban energy management. The transition from landscape to digital twins is a step toward more integrated, data-driven ways to understanding and regulating urban energy systems. Geospatial datasets can be used with energy models and digital technology to create more precise, dynamic, and scalable solutions to the energy problems that modern cities face. This study adds to the expanding this interdisciplinary subject by presenting a geospatial framework for the development of Energy Digital Twins, with the goal of promoting sustainable, efficient, and resilient urban built environments.

1.1 Why there is the need of this research ?

The management of energy systems in urban built environments presents a variety of issues due to the complexity, scale, and variability of cities. Urban environments have a wide range of building designs, construction materials, and usage patterns, all of which have a distinct effect on energy consumption (Y. Li & Feng, 2025b; Y. Wang et al., 2024) . This diversity makes it challenging to design dependable and scalable energy system management solutions. Accurate representation of building attributes, including geometry, material properties, energy consumption profiles, and interactions with the surrounding environment, is critical for any meaningful assessment of energy performance (Oraiopoulos & Howard, 2022) . However, gathering and integrating such precise information on an urban scale remains a significant issue. These restrictions impede the efficiency of current Sustainable Energy Management Systems (SEMS), emphasizing the need for better approaches that can use advanced geospatial datasets consistently and operationally(Y. Li & Feng, 2025a).

Over the last decade, Energy Digital Twins (EDTs) have emerged as a possible solution to some of these limitations of SEMS. EDTs are virtual equivalents to physical energy systems in the built environment, allowing for

continuous monitoring, modelling, and optimization of energy consumption (Ba et al., 2025). By combining physical building attributes with operational energy data, EDTs provide a framework for assessing energy performance in both spatial and temporal dimensions (Rojas-Colmenares et al., 2025). This advantage of an operational EDT supports better decision-making, increases energy efficiency, and makes it easier to integrate renewable energy sources. Despite these benefits, the construction of accurate EDTs is still heavily reliant on the availability, quality, and level of information in input data (Chidiebube Igbokwe et al., 2025; Mbasso et al., 2025a). The extraction and integration of building-related information from geospatial databases comes with the major technical obstacles, limiting EDTs' broader implementation in urban situations (X. Liu et al., 2017).

One of the key issues stems from the inherent complexity of urban built areas, as they are made up of buildings with different geometries, orientations, construction materials, and energy systems across different types of constructions (Kandelan et al., 2024). These variations in the built environments have a direct impact on heating, cooling, and total energy demand. The heterogeneity of geospatial datasets makes it challenging to accurately capture such traits. Microclimatic variables such as shade impacts, wind patterns, and heat exchange between nearby structures all have an impact on urban environments (Hossain et al., 2025; Lopez-Cabeza et al., 2025). These microclimate factors add uncertainty to energy modelling procedures and the current SEMs frequently do not adequately account for these factors, owing to limits in data resolution and modelling capabilities (Duan et al., 2025). As a result, techniques that can combine comprehensive spatial information while also accounting for complicated environmental interactions inside urban contexts are needed.

Another major issue is the reliability and consistency of building data from heterogeneous geospatial data sources (Aghazadeh Ardebili et al., 2024; Koldasbayeva et al., 2024a). A range of different geospatial datasets such as Geographic Information System (GIS) data layers, LiDAR point clouds, and Building Information Models (BIM) include useful information about urban structures including their layouts, building elements, geometric and textural information (Y. Li & Feng, 2025a). However, these geospatial datasets are often generated in different standards and formats resulting in errors in data representation (Antonioni, 2023; Koldasbayeva et al., 2024a). This lack of standardisation makes it difficult to integrate many data sources and reduces the reliability of the models obtained (Hernández-Herráez et al., 2025). Furthermore, the extraction of energy-relevant features such as windows, rooftops and window -

to-wall ratios is a challenging task requiring advanced procedures with computational algorithms(Meng et al., 2026). These are critical features in predicting building energy performance, but they are not commonly available in most geospatial datasets. Thus, the difficulty in obtaining such information inhibits the use of EDTs in large-scale urban energy investigations. When several data sources are combined, the generation of EDTs becomes more complex. While geospatial datasets contain precise information about the physical and structural properties of urban environments, they generally do not include direct data about energy consumption and system dynamics(Nowacka & Remondino, 2018). However, data acquired through energy audits, smart meters, sensor networks provide information on energy consumption but are often not geospatially tagged or precise(Roney Bernardes, 2024). These disparate data points must be linked to build comprehensive and accurate digital twins of urban energy systems. However, differences in data resolution, time availability and collection methods introduce uncertainties that can affect the accuracy and performance of the model(Ekström et al., 2021). Satellite images can cover large areas but do not provide the level of detail needed for building level analysis. LiDAR and photogrammetric data provide high resolution geometric and textural information but require substantial processing to extract relevant features(Chajaei & Bagheri, 2025; Hakim & Tsai, 2026). These geospatial datasets challenges require the development of robust data fusion techniques that can integrate heterogeneous information, ensuring consistency and reliability.

The additional limitations of the geospatial datasets are the absence of the direct semantic information which are essential for deriving analysis for any kind of applications(Mallet & Raimond, 2026) . While datasets like LiDAR point clouds and photogrammetric models provide rich physical and textural information, they do not automatically include semantic descriptions of urban elements. For example, raw point cloud data does not clearly indicate whether parts relate to windows, doors, or other structural components. Extracting this data necessitates computationally intensive classification and segmentation techniques that frequently involve trade-offs between accuracy and efficiency. The lack of semantic enrichment limits the utility of geospatial data for energy modelling because critical elements such as material properties, insulation characteristics, and building component distributions must be extracted through additional processing processes(Jeddoub et al., 2025; T. Zhang et al., 2025). These factors complicate the development of EDTs and adds potential errors to the procedure of EDT development.

However, integrating energy metrics and data with static geospatial information raises issues such as data interoperability, synchronization, and computational efficiency. Existing data integration approaches are frequently computationally demanding or unable to maintain consistent alignment across multiple data sources. Moreover, modelling of correlations between architectural, environmental and energy systems requires more advanced computational methods that combine data-driven and physics-based approaches. These criteria indicate the need for structured frameworks to manage complex data interactions in EDTs.

The development of urban energy systems poses questions about the long-term scalability and sustainability. As cities grow and adapt, energy consumption patterns shift, and new data sources emerge. Keeping EDTs up to date and adaptable to these changes is a huge problem. Continuous data collection from IoT devices and remote sensing platforms can improve temporal resolution, but it also increases the volume and complexity of data that needs to be processed and examined. Creating effective data pipelines for processing large-scale, real-time geospatial and energy data is thus critical for the actual deployment of EDTs at the city scale. Given these constraints, there is an obvious need for a thorough and methodical framework for the development of Energy Digital Twins for urban built environments. This framework must solve problems like as data extraction, integration, semantic enrichment, and real-time processing. It should also offer scalable solutions that may be deployed in a variety of urban settings while preserving accuracy and reliability of the building elements. This need is addressed in the present study by proposing a geographic framework for the generation of Energy Digital Twins. The goal is to develop operational techniques for extracting and fusing significant building components from advanced geospatial datasets to improve the representation of urban energy systems. The proposed framework aims at enabling the efficient energy management strategies and contributing to the reduction of energy consumption and carbon emissions in urban areas through enabling more accurate modelling and analysis. Furthermore, the integration of real-time data and predictive modelling features into EDTs can assist demand-side management and smart grid applications and reduce dependence on traditional energy sources.

On a larger scale, the development of such frameworks contributes to global sustainability goals. Improved urban energy management helps to deliver the goal of access to clean and efficient energy and also to the goal of sustainable and resilient cities. This paper provides the foundation for the development of digital

technology for urban energy systems by solving current bottlenecks in data integration and modelling. Therefore, the shift from landscape to digital twins is not only a breakthrough in technology, but also a necessary step for sustainable urban growth.

1.2 Research Gap

The development of sustainable energy management systems for urban built environments has received increased attention in recent years, owing to the advancement of geospatial technology and digital modelling methodologies. Despite these developments, numerous constraints remain in the integration of geospatial datasets with energy modelling procedures, limiting the practical implementation of Energy Digital Twins (EDTs) on an urban scale. Existing research has focused on field components such as building energy simulation, geospatial data processing, and digital twin concepts, but a comprehensive and operational framework that systematically links these components is still in early stages of development of EDTs (Iossa et al., 2025; S. Wang et al., 2026).

One of the key limitations is the lack of standardized methods for discovering and utilizing geospatial datasets for energy modelling purposes (A.H. Selmy et al., 2024; Koldasbayeva et al., 2024b). Although GIS, LiDAR, and photogrammetric point clouds are datasets with rich geographical information, there is no consensus on the specific data requirements and specifications needed for EDT development. These differences in data format, resolution and acquisition result in variations that limit interoperability and reproducibility. Hence, the existing frameworks are based on case-specific data processing approaches that are not easily transferable to different urban contexts. This emphasises the importance of a systematic framework that defines the necessary data resources and their properties for robust EDT development.

Another research gap identified is the extraction and representation of building elements that are important for energy modelling. The importance of building geometry and physical qualities is well known, but relatively little has been done to systematically extract features such as windows and rooftops from airborne point cloud datasets (Dawood et al., 2017; Dey et al., 2023; Ren et al., 2024). These building features have a significant impact on energy performance, impacting heat exchange, solar gains, and renewable energy potential (Zhou & Hu,

2025). However, the existing feature extraction algorithms are either insufficiently accurate or computationally intensive, making them impossible to employ on a greater scale of an urban city (J. Zhang et al., 2022). Besides, the lack of uniform processes for converting retrieved characteristics into energy modelling inputs limits their practical application in EDT systems (Pan et al., 2023).

The impact of data quality and resolution, specifically point cloud density of the point clouds, is another area where current study related to digital twins is limited (Kaiser & Dědič, 2024; Osadcha et al., 2023). While high-resolution datasets are widely considered to improve feature extraction accuracy, there has been no systematic research into how differences in point density affect the dependability of derived architectural features (Crommelinck et al., 2016; Kaiser & Dědič, 2024). This adds uncertainty to the search for the best combination of data collecting costs, processing requirements and modelling accuracy. Although machine learning and deep learning approaches for point cloud processing have made substantial advancements in recent years, their application to building feature extraction for urban energy modelling has not yet been explored (Maru et al., 2023). Existing research mainly focuses on improving classification accuracy, but neglects computing efficiency and scalability which are important for large-scale urban applications. Also, there is little comparative examination of different approaches' usefulness for extracting energy-relevant architectural attributes (Xu et al., 2024). These factors limit the ability to find the procedures that can be successfully integrated into an operational EDT framework.

Another gap occurs in the integration of retrieved geospatial data with energy modelling tools. Current techniques frequently regard data processing and energy simulation as distinct processes, resulting in disconnected workflows that limit the use of digital twin applications in energy sector (Ba et al., 2025; Subramanian & Stonier, 2026). The lack of seamless integration between geospatial data and energy models limits the ability to conduct real-time analysis, scenario simulation, and continuous system monitoring (Koirala et al., 2024a; Y. Li & Feng, 2025a). This discrepancy highlights the necessity for a unified framework that integrates geographic data collecting, feature extraction, and energy modelling into a cohesive system.

While the concept of digital twins has been widely debated, its actual application to urban energy systems is still in its earliest phases. Many existing research are conceptual or limited to small-scale applications, with insufficient

operational depth for real-world deployment. There is a need for research that not only produces theoretical models, but also shows how they may be applied in a real-world urban setting. The research gap for this doctoral research is defined by the lack of an integrated, and data-driven framework for the development of the Energy Digital Twins that efficiently use geospatial datasets for urban energy systems management. To address these limitations, data standards, feature extraction, building features method evaluation, and model integration must all be done in a systematic manner. This research study intends to fill up these research gaps to an extent by developing an operational framework that integrates these energy metrics, geospatial components, contributes to the increasing the use of digital twin technologies in sustainable urban energy systems.

1.3 Scientific relevance and scope of the research

The concept of Energy Digital Twins (EDTs) is gaining prominence as an important tool for SEMS in urban built environments. EDTs' scientific value arises from its ability to generate exact virtual reproductions of physical buildings and energy systems, allowing for precise simulations, predictive analytics, and real-time optimisations (Almadhor et al., 2025; Roman et al., 2025). With the growing global demand for energy-efficient infrastructure, EDTs provide a link between virtual 3D city models and real implementations by combining advanced geospatial datasets, Building Information Modelling (BIM), and energy metrics data (Francisco et al., 2020; Jovanović et al., 2020; Zhao et al., 2021). This technological advancement aids in the development of smart cities and increases energy efficiency by reducing waste and boosting demand-response techniques. The CityGML database acts as a central hub, combining city maps with data on solar energy, heat, and power grids to build an Energy Digital Twin (Agugiaro et al., 2018; Koirala et al., 2024b; Lam et al., 2024). EDTs helps cities analyze their energy needs and manage their infrastructure more effectively in one digital space. Figure 1 below shows the different elements of an operational EDT system.

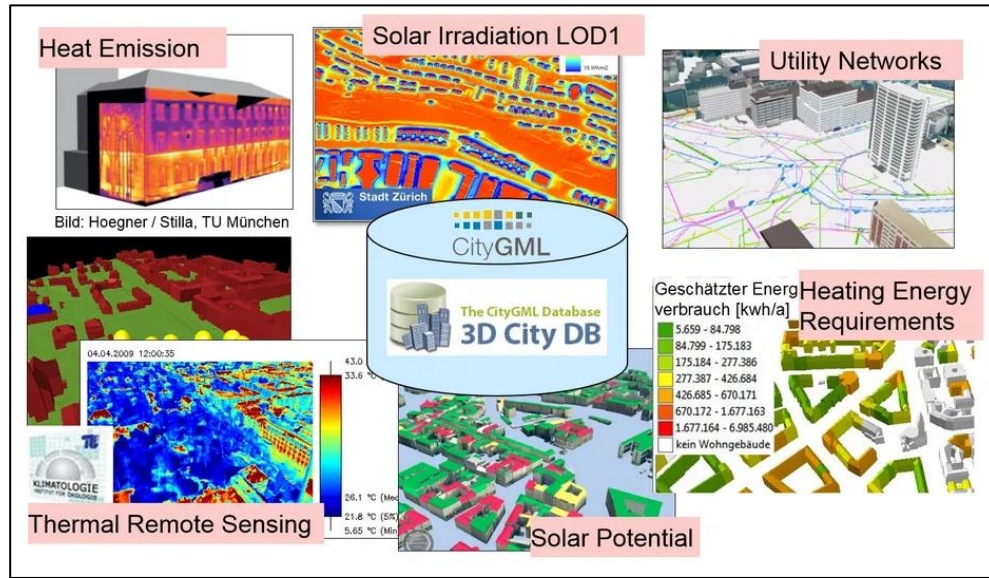


Figure 1: Illustration of connected EDT elements, taken from (Chair of Geoinformatics Technical University of Munich, 2025) .

The ability to extract and incorporate significant building features affecting energy consumption is a core feature of EDTs, including geometric properties such as windows, doors, rooftops, floor area, volume, and building features orientation, thermal properties such as insulation levels, window-to-wall ratio, and the operational factors such as HVAC system performance, occupancy patterns (Arowoiya et al., 2024; Yüksek & Karadayi, 2017). EDTs can be developed by combining advanced geospatial datasets such as point clouds from aerial and terrestrial Light Detection and Ranging (LiDAR), aerial photogrammetry, Geographic Information System (GIS) layers, and energy indicators(Iossa et al., 2025; Roman et al., 2025). The integration of various datasets assures that energy models are not only spatially accurate, but also capable of adapting to changing environmental variables such as weather patterns and urban heat islands(Richiardi et al., 2025). Figure 2 below presents an Energy Digital Twin (EDT) from the city of Gothenburg in Sweden with an interface visualizing city's urban infrastructure, and building-specific final energy consumption metrics. EDTs in such applications facilitates predictive scenario modeling by integrating GIS layers with climate variables, allowing for data-driven analysis of renovation potential and energy efficiency across the city.

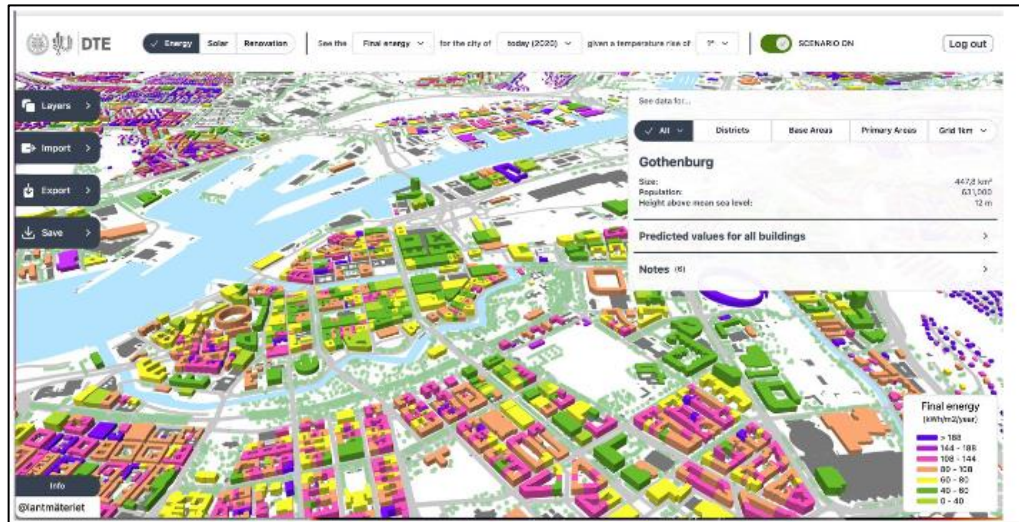


Figure 2: An Illustration of an EDT as a system from the city of Gothenburg, Sweden, taken from (Maiullari et al., 2023).

Another scientifically relevant element of EDTs is their ability to perform predictive and prescriptive analytics. EDTs use artificial intelligence (AI) and machine learning (ML) algorithms to simulate various energy scenarios, allowing urban planners and policymakers to evaluate the impact of various energy policies and building retrofitting schemes (U. Ali et al., 2024; Onma Enyejo et al., 2024). These predictive capabilities facilitate decision-making in energy conservation and carbon footprint reduction, both of which are critical components of climate change mitigation methods. Furthermore, the constant feedback loop between the physical environment and the digital twin keeps energy models current and sensitive to changes in building operations and outside influences (Cina et al., 2025). Figure 3 below presents an overview of the scientific relevance of EDTs in urban environments and how different areas are connected to an EDT in operation.

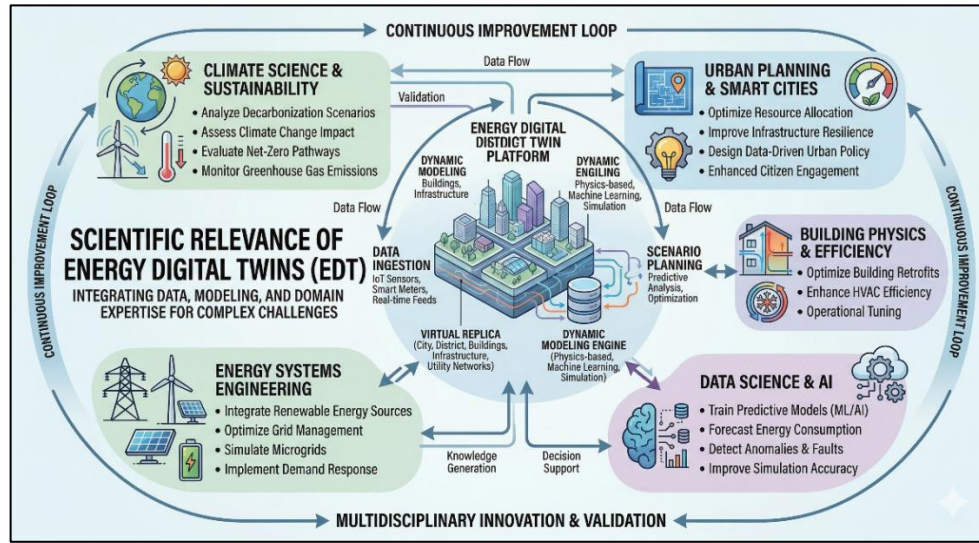


Figure 3: Scientific relevance of Energy Digital Twins in built environments, information from (H. Du et al., 2024; Venkateswarlu & Sathiyamoorthy, 2025)

EDTs are scientifically more valuable because they are cross-disciplinary and incorporate ideas from cutting-edge geospatial research, energy engineering, computer science, and urban planning. This combination of fields allows a holistic view of energy management, considering the spatial, temporal, and behavioural dimensions of energy consumption. Standardising data collection, processing and visualisation techniques in EDT development research also improves repeatability and scalability, enabling the use of these models in different urban contexts (Padsala et al., 2025). The development of EDTs signifies a prominent scientific accomplishment in the quest for sustainable and resilient urban energy systems inside an urban framework.

With increasing global applicability, Energy Digital Twins provide various practical applications in the sustainable control of energy systems in urban built environments. EDTs can help identify inefficiencies in lighting, HVAC and other energy-consuming systems by combining real-time sensor data with historical energy consumption trends (Ba et al., 2025). This feature enables the facility managers to use some energy saving strategies and consequently decreases the total energy consumption and operational cost. Additionally, EDTs can be combined with predictive maintenance methodologies to anticipate system failures and schedule repairs promptly, thereby prolonging the lifespan and improving the performance of the building infrastructure. Another major application is in the urban energy planning and policy making where

municipalities and urban planners can use EDTs to model energy flows within neighbourhoods and districts, enabling the development of energy efficient zoning regulations and deployment of smart grid systems(Hussein & Basel, 2024). EDTs can assess the impacts of renewable energy integration, such as photovoltaic (PV) panel and wind turbines, by analysing the spatial and temporal variations in energy supply and demand(Majidi Nezhad et al., 2025). These insights enable the design of resilient urban energy networks that optimise the use of renewable energy and ensure grid stability.

EDTs are capable of significantly improving occupant comfort and indoor environmental quality. By persistently assessing indoor temperature, humidity, air quality, and occupancy patterns, EDTs can enhance building management systems to foster a comfortable and healthy indoor atmosphere while minimising energy use(Arowoia et al., 2024; Zhou & Hu, 2025). This use is particularly beneficial for extensive business edifices, educational establishments, and healthcare institutions where sustaining optimal indoor conditions is essential for occupant health and productivity. EDTs possess a significant advantage in retrofitting and remodelling endeavours aimed at enhancing the energy efficiency of existing buildings (S. K. Sharma et al., 2022). Prior to executing alterations in the physical urban environments, municipalities might make use of the digital twins of deteriorating structures to evaluate diverse retrofitting options, like enhanced insulation, window substitutions, or HVAC enhancements(Villani et al., 2025). This approach mitigates the likelihood of unprofitable investments while guaranteeing that energy conservation efforts are grounded on data analysis. Moreover, EDTs facilitate adherence to energy performance mandates and certification criteria by delivering accurate and validated energy evaluations.

EDTs are an innovative approach to sustainable energy management in urban structures and their scientific significance derives from their ability to integrate geographic datasets, automated AI-driven analytics, and real-time monitoring to produce dynamic and accurate energy models (Aghazadeh Ardebili et al., 2024; Cespedes-Cubides & Jradi, 2024; Mbasso et al., 2025a). EDTs are utilised for building-level energy optimisation and extensive across the city energy planning, offering significant potential to reduce energy consumption, enhance tenant comfort, and support the transition to low-carbon cities. As research in these areas advances, EDTs are poised to become essential instruments for attaining energy sustainability in contemporary urban environments.

1.4 Research Objectives and Questions

The primary objective of this research is to establish a comprehensive geospatial framework for the establishment of an Energy Digital Twin (EDT) system in Torino, facilitating the analysis, monitoring, and planning of urban energy demand. The study aims to establish a systematic and practical framework for converting urban environments into data-driven digital models of energy systems. This involves carefully locating, retrieving, integrating, and employing geographical data to develop an EDT that can precisely and scalable characterise the physical and energy-related attributes of the built environment.

A critical part of this research is the identification and establishment of the key data resources that are necessary to build an operational EDT system. The effectiveness of an EDT is dependent on the availability, quality and compatibility of many data sources describing building geometry, structure and energy performance. These include datasets of aerial point clouds from photogrammetry and LiDAR, Geographic Information System (GIS) data, and other datasets on energy use and environmental factors. The work aims at describing basic properties of those data sets, like their geospatial resolution, point density, temporal consistency and semantic content, which are necessary for a reliable energy modelling. To be able to apply the developed framework consistently in different urban settings, the criteria need to be defined while retaining the required level of detail for analysis at building level.

The study aims at identifying data specifications and identifying fundamental architecture elements necessary for energy modelling in an EDT framework. The windows and rooftops are among specific physical attributes that are closely associated with the building energy efficiency. Windows can influence solar heat gains, daylight penetration and thermal losses. Roofs are important to understand heat exchange mechanisms and evaluate the possibility of renewable energy production, especially by solar systems. This study focusses on the extraction and parameterisation of these two features from airborne point cloud data to produce useful inputs for energy modelling. The research aims at revealing the important issues related to these elements, such as their geometric dimensions, orientation and distribution and developing methods of their direct acquisition from the geospatial data.

The extraction of architectural elements from point cloud datasets is confronted with many technical challenges, especially in terms of data quality and

processing complexity. The main purpose of this research is to study the effect of point density on the accuracy of feature extraction. The amount of information contained in a point cloud depends on the density of points. This in turn affects the ability to identify and trace structural elements such as windows and rooftops. Datasets with low density may not provide the optimal or appropriate feature representation, whereas datasets with high density require more computer resources and processing time. The correlation between point density and extraction accuracy is studied to find the optimal parameters that strike a balance between data quality and computational efficiency. The findings of this study enhance the methods of data collection and processing suitable for large scale urban applications.

An objective of this research is to evaluate and identify suitable computational methods for feature extraction from point cloud data. The prior art comprises a variety of machine learning (ML) and deep learning (DL) approaches for point cloud classification and segmentation. However, these methods vary in their geometric fidelity, computational cost, and applicability to different urban settings. The aim of the present work is to evaluate these tactics for feature extraction development in EDT, focusing on those that can offer the best accuracy/efficiency trade-off. The evaluation includes aspects such as the ability to generalise across datasets, sensitivity to changes in data resolution and scalability to large urban areas. The aim of this assessment is to provide a systematic framework for the automatic extraction of energy relevant building features.

The proposed EDT system is characterised in its core by the integration of collected architectural features within an energy modelling framework. The study aims to define ways of coupling energy performance indicators with geometric and semantic data of geographical databases. That is, transforming raw geographical data into structured inputs for energy simulation models. The integration process must ensure consistency of data sources and keep the spatial relationships required to represent the interactions between buildings and their environments. The EDT framework integrates physical and energy related features. It allows to simulate energy flows, assess the build performance, and evaluate different energy management scenarios.

The EDT of the urban environments is an example of an operative implementation of the proposed framework. The goal is to develop an operational system which can be used for real life applications for urban energy management.

This includes the ability to review current energy usage trends, track system performance over time, and assess the potential impact of possible interventions, such as energy conservation or the adoption of renewable energy technologies. The EDT is perceived as a comprehensive decision-making instrument, able to work at different scales from single structures to the urban scale. The implementation phase includes the collection of relevant datasets, the use of feature extraction techniques and the integration of energy modelling components into an integrated digital framework.

The study also aims at assessing the impact of the developed framework on sustainable urban energy management. The EDT system will improve the accuracy and availability of energy data and information for better planning and policy making. The possibility to simulate different scenarios enables stakeholders to evaluate the potential outcomes of different strategies like building upgrades, optimisation of energy distribution or higher utilisation of renewable energy. It reduces energy use and greenhouse gas emissions, and it makes urban energy systems more resilient. The research is intended at ensuring both the scalability of the proposed framework and its adaptability in various urban environments. Even though the case study is located in Torino, the methodologies and protocols developed are meant to be relevant for other cities with different data availability and urban characteristics. This includes the development of specific methods of data processing, feature extraction and model integration. The paper proposes a clear and reproducible methodology allowing for the extensive use of the Energy Digital Twin technologies in the city energy management. The aim of this work is to present a geospatially enabled framework for Energy Digital Twins that combines data gathering, feature extraction and energy modelling in one system. The broader research objectives are the identification of relevant data sources, extraction of relevant building characteristics, evaluation of computational approaches and implementation of an EDT for the urban built environments. The project intends to enhance the use of digital technology within urban energy systems and to offer practical solutions for sustainable and efficient energy management in the built environment. This research is aimed at one primary research objective of development of an EDT framework and the research questions listed below are investigated in-line of this doctoral research:

Primary Research Objective: To develop a geospatial framework for the development of an Energy Digital Twin (EDT) to support the analysis, monitoring, and planning of sustainable urban built environments.

RQ_1: What are the fundamental data resources and their specifications needed to develop a robust and functional Energy Digital Twin for the urban built environments?

RQ_2: Which building characteristics are essential for energy modelling in an EDT framework and how these characteristics can be systematically extracted from the geospatial datasets?

RQ_3: How does variation in point cloud density affect the accuracy of extracting building features from point clouds for the purpose of energy modelling?

RQ_4: Which advanced computer vision techniques offer an optimal equilibrium between geometric precision, computational efficiency, and adaptability for extracting architectural elements from point cloud data in the context of EDT development?

1.5 Research Contributions and Novel aspects of the research

This research enhances urban energy modelling by developing a comprehensive geospatial framework for applications of Energy Digital Twins (EDTs) in urban built environments. This work addresses essential constraints in data integration, feature extraction, and energy modelling by developing an operational methodology that links geographic datasets to energy system representation. The research work address theoretical and practical problems related to the development of EDT with geospatial enabled and scalable data-driven methods for sustainable urban energy management.

This study is important, as it provides a comprehensive conceptual framework that outlines the types of methodologies needed to generate an EDT using different geospatial resources. This study proposes a unified workflow of data collection, feature extraction and energy modelling, which is different from the existing systems that treat data processing and energy modelling independently. The framework delineates the roles and standards of several datasets, including airborne point clouds, GIS data, and energy-related information, to guarantee consistency and usefulness during the EDT development process. A significant

enhancement is the methodical extraction and depiction of building components necessary for energy modelling. The research emphasises windows and rooftops as significant determinants of building energy efficiency. Techniques are being developed for the direct extraction of these features from airborne point cloud datasets, which can then be used to produce complete and geospatially explicit inputs for energy models. This removes the requirement of ambiguous building data and allows for a broad spectrum of urban applications.

The study explores the relationship between point cloud density and the accuracy of feature extraction. The work studies the effect of varying point density on the detection and characterisation of architectural elements, highlighting the trade-offs between data quality and accuracy of the building features extraction from the geospatial datasets. This provides criteria for choosing suitable datasets to be used for the development of EDTs, especially in the large urban environments. The work also considers machine learning and deep learning approaches for point cloud analysis, highlighting their ability to extract energy-related architectural components. The evaluation is based on geometric accuracy, computational efficiency and adaptability to different datasets. This offers a practical platform for identifying those methods which can be effectively assimilated into the development of an operational EDT framework. The integration of the acquired geospatial data in the energy modelling methods is a major improvement in this work. This work discusses methods for transforming geospatial datasets into structured inputs to energy calculations. This integration allows to represent energy dynamics in a geospatial context, which improves the understanding of the interaction of buildings with their environment.

The novelty of this study is the integration of geospatial data processing, feature extraction and energy modelling in one holistic operational framework. The study exploits independent methods with explicit linkages among data sources, computational methods and representations of energy systems. This holistic methodology improves the scalability and reproducibility of the development of EDT for many urban contexts. The summary of the key contributions of this research is as follows:

- Development of a geospatial framework for the development of Energy Digital Twins in urban environments
- Identification and specification of essential geospatial datasets and data requirements for EDT development

- Establishment of operational workflows for extracting building features from the geospatial datasets
- Investigation of the impact of data resolution on feature extraction accuracy and energy modelling reliability
- Evaluation of machine learning and deep learning methods for efficient and scalable point cloud processing
- Integration of geospatial data with energy modelling inputs for improved representation of urban energy systems

1.6 Structure of the thesis

This dissertation comprises eight chapters. Chapter 1 delineates the research, elucidating the research topic, its scientific significance, and prospective applications, concluding with the research objective and the questions posed. Chapter 2 examines the current literature on digital twins for urban settings, energy digital twins, their progression and relevance over time, techniques for extracting windows and rooftops from point clouds within the framework of energy digital twins and offers a comprehensive overview of the present state of digital twin development. Chapter 3 delineates the worldwide practical implementations of digital twins and their significance in sustainable urban planning. Chapter 4 describes the methodology and the different procedures used in this research. Chapter 5 describes the datasets, acquisition systems and software tools used in the study. Chapter 5 presents the results of the research approach application on the datasets and their interpretations. The findings of the study are examined and critically analysed in Chapter 7. Finally, Chapter 8 concludes the thesis with answers to the research questions, highlights of the key findings, discussion of limitations and suggestions for further research. Supporting research activities conducted during the research with appropriate citations in the text are placed at the end of the thesis in the form of appendices. The thesis structure is summarized in Table 1 below.

Table 1: Structure of thesis document

Chapter No.	Description
1	Research Introduction
2	State of the Art of Digital Twins: a Literature review
3	Practical Implementations of Digital Twins across the world
4	Conceptual Framework, Methods and workflows adopted
5	Study Area, Dataset Acquisition Systems, and processing tools
6	Outcomes of the research
7	Discussions and research implications
8	Takeaways and Conclusions

Chapter 2

The state of the art : Review of the existing studies

The Digital Twin (DT) represents a significant advancement in how we understand and manage physical processes and systems across the multiple applications (Cureton & Dunn, 2020). It functions as a dynamic digital replica of a real-world object, process, or system, constantly updating with associated data from its physical counterpart, depending on its specific use case. This constant relationship between the physical world elements and digital replica allows for extensive analysis, precise predictions, and superior decision-making across a wide range of applications of DTs (Ferré-Bigorra et al., 2022). While the concept of DTs has been widely accepted in a variety of industries, this analysis focuses on their origins, development, and, most crucially, application in a geospatial context, specifically for sustainable energy systems for urban environments (Koirala et al., 2024a; Majidi Nezhad et al., 2025).

The formal word "Digital Twin" first appeared in the early 2000s, primarily in manufacturing and product lifecycle management (Mylonas et al., 2021). The idea was to create a complete digital replica of a manufactured item that would track its physical counterpart throughout its lifetime (Attaran et al., 2023). This comprises everything from the initial design and manufacturing to the use, maintenance, and eventual disposal. This early emphasis highlighted the significance of a steady stream of data for improving performance and projecting how things would work, mostly for specialized industrial items in controlled

situations. While these early concepts did not directly include geography, they did emphasize the significance of strong data links and accurate models, laying the groundwork for future integration with location-based information.

The rapid expansion in the amount of geospatial data that could be collected and evaluated represented a watershed moment in the evolution of the Digital Twin concept. The state of art Earth Observation (EO) technologies, including high-resolution satellite images, airborne photogrammetry, LiDAR (Light Detection and Ranging), and drone-based photography, have produced massive amounts of detailed location-based data (SPARC Faculty, 2023). Simultaneously, Geographic Information Systems (GIS) developed into sophisticated tools for storing, processing, and visualising spatial data. They grew become useful instruments for replicating large, complex geographical areas. This significant advancement marked the shift from single-object Digital Twins to geospatial-focused Digital Twins, in which physical location, spatial relationships, and environmental context were essential and distinctive characteristics of the digital replica(Cárdenas-León et al., 2024; Somanath et al., 2024).

Within this geospatial context, there has been a strong emphasis on using Digital Twins to improve building energy performance. Buildings, as fixed structures in specific locations, are significant energy consumers and producers to emissions. To use energy more efficiently in buildings, one must first understand their physical qualities, how they function, and how they interact with the urban and natural ecosystems around them. The specialised Energy Digital Twins for buildings by combining comprehensive geometry data, which is typically obtained from point clouds with actual energy use data, readings from environmental sensors, and even information on how people use the facility (Mbasso et al., 2025b).

This chapter is a comprehensive review of the previous studies related to the domain of this research. It starts with a definition of Digital Twins and traces their evolution from first ideas to formal definitions. We then discuss their evolution over time and highlight major milestones that have extended their reach. Much of it is about how Digital Twins are used in a geospatial context. In particular, the use of spatial data and remote sensing technologies to support the construction of Digital Twins. The chapter discusses then the different applications of Digital Twins, especially the generation of EDTs from the geospatial datasets. This chapter seeks to synthesise the existing research works to identify gaps in research and to develop a sound theoretical framework. Such preparation will enable the

proposed study to make a meaningful contribution to the improvement of building energy efficiency using advanced geospatial Digital Twin technologies. In this chapter, the concept of digital twins has been discussed, with a special focus on their origin, evolution and applications in the fields of geospatial technology and sustainable energy systems in urban environments.

2.1 Digital Twins : Origin and evolution with time

Digital Twin (DT) technology, a prominent framework for generating virtual representations of physical elements, has undergone remarkable growth across various sectors. In geospatial context, DTs as the digital reproductions provide an extensive comprehension of physical objects or systems within their spatial environment (Ketzler et al., 2020).

2.1.1 The Genesis of Digital Twins: From Concept to Reality

The notion of a “digital twin” was first introduced in the early 2000s, although similar ideas had been suggested before under different names (Semanjski, 2023). The idea is generally attributed to Michael Grieves at the University of Michigan in 2002, within the Product Lifecycle Management (PLM) context, with the formal introduction of the idea at a Society of Manufacturing Engineers convention (D’Amico et al., 2022). The starting point was to have one digital description of a physical product through its whole life cycle from design to final disposal. The basic idea was to connect one physical object with its virtual counterpart, so that they can exchange information all the time. Previous variations of this idea were mostly conceptual, demonstrating the potential for enhanced product design, manufacturing processes and servicing (N. Sharma, 2025). However, the technology of the time, particularly the constrained computational power and the limited data integration capabilities, hampered its rapid widespread adoption. Additionally, technological progress (sensor technology, data storage and processing) makes the practical application of digital twins more feasible.

Over the years, the core idea has developed from single products to more complex systems and processes. Digital twins have moved from simple digital models or simulations to dynamic, real-time representations that interact with their physical counterparts (Simio Staff, 2025). In some cases, IoT helped to

create this dynamic linkage, allowing a seamless data exchange between physical domain and digital twin and vice-versa. The more advanced digital twin technology enabled two-way data transmission, which made it possible to monitor, control and optimise physical systems.

2.1.2 Defining the Digital Twin in a Geospatial Context

A Digital Twin (DT) is a virtual representation of a physical object, element or system, created to observe, analyze, and enhance its behaviour and attributes (AlBalkhy et al., 2024; Barricelli et al., 2019; ISO/TC 211, 2020). A Spatial Digital Twin (SDT), or a digital twin in a geospatial context, highlights the spatial and dimensional attributes of the physical item, offering an in-depth comprehension within its geographical context (M. E. Ali et al., 2024). This entails the integration of accurate location data, three-dimensional models, and additional geographically related information to construct a comprehensive, spatially aware virtual world.

The fundamental elements of any digital twin are data, models, and networks and they are particularly vital in the geospatial sector (Peldon et al., 2024b). In a geospatial setting, "twin data" denotes the extensive collection of geospatially labelled information received from diverse sources. This encompasses satellite photos, aerial photographs, LiDAR scans, sensor data from IoT devices, and conventional GIS (Geographic Information System) datasets. (Ferré-Bigorra et al., 2022) The quality and timeliness of this data are crucial for the correctness and efficacy of the geographic digital twin. The "twin models" are the virtual representations themselves. These include simple 2D maps, detailed 3D geometric models, semantic data about urban characteristics, terrain representations, and environmental simulations. These models are often dynamic and updated as new data is received, sometimes in real time or near real time, to reflect the real world's actual condition. These models can vary in complexity from high-fidelity representations for accurate engineering analyses to reduced-order models for extensive urban planning applications. "Twin networks" are a means of communication and interaction between the physical geospatial environment and its digital copy. This necessitates a reliable communication infrastructure to process large amounts of sensor data, real-time model updates and the distribution of processed information to users and applications. Secure and efficient real-time communication within the geographic digital twin systems demands advanced

networking capabilities, particularly the future development of 6G networks. A key trend in the growth of digital twins in geospatial is the enhanced integration with new technologies. Artificial Intelligence (AI) and Machine Learning (ML) are crucial for the analysis of large geographical data, trend identification and enabling predictive analytics in the digital twin. For example, AI systems could predict traffic congestion by analysing real-time vehicle data embedded in a city's digital twin or forecast energy use in a given urban area.

The Internet of Things (IoT) is the essential conduit for gathering real-time data from various sensors distributed over a geographical area, thereby supplying information to the geospatial digital twin (Allam et al., 2022). This might include air quality sensors, traffic cameras, smart streetlights and utility meters, all contributing to a dynamic, real-time virtual representation of an urban area. Blockchain technology is being explored for its potential to enhance data security, transparency, and interoperability within geospatial digital twin ecosystems, especially for the management of complex data lifecycles (Nielsen et al., 2020; Prasanth et al., 2025). To date, DT implementations can be found in different domains such as urban planning, environmental monitoring, infrastructure management and disaster response (AlBalkhy et al., 2024; Barricelli et al., 2019; Botín-Sanabria et al., 2022). Recent DT solutions increasingly leverage vast amounts of data, including high-resolution satellite imagery, real-time sensor data, IoT networks, and complex GIS datasets, to create accurate virtual representations of physical environments (Dihan et al., 2024). For example, city-scale digital twins such as Virtual Singapore and Helsinki 3D provide interactive platforms for stakeholders to visualise urban scenarios, simulate environmental changes, and optimise urban planning decisions (Y. Du et al., 2024; Hämäläinen, 2021). The different critical elements of a functioning digital twin system are presented in Figure 4 below.

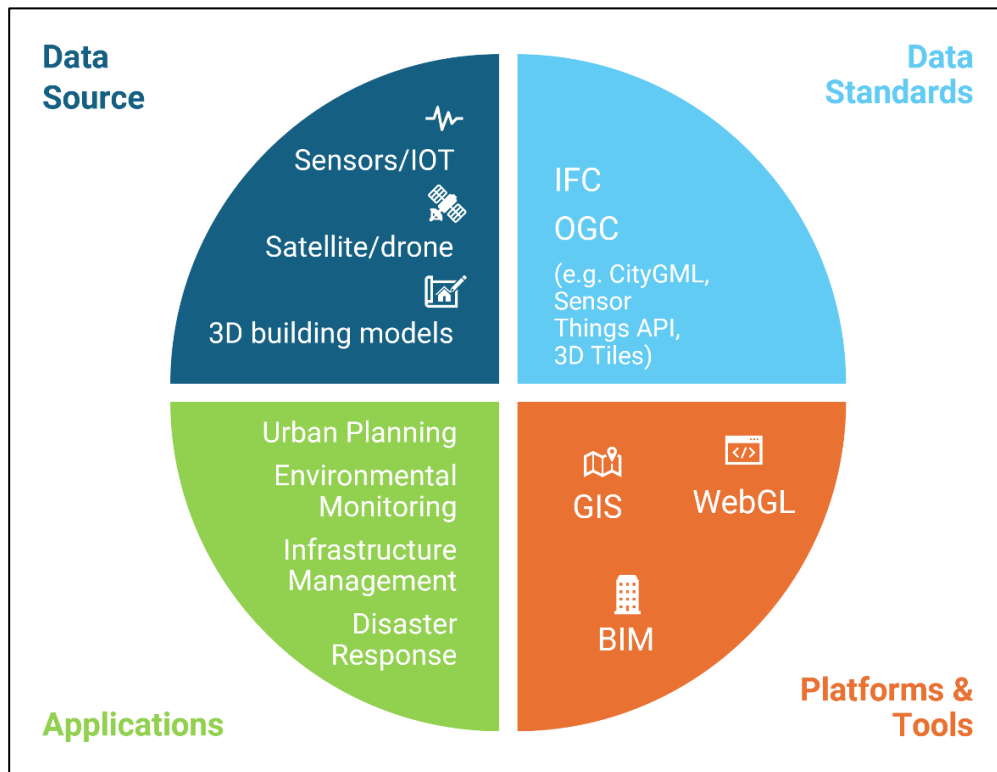


Figure 4: Various elements of a functional digital twin system

2.1.3 The Evolution of Geospatial Digital Twins: From GIS to Dynamic Insights

The evolution of modern geographic digital twins has encompassed multiple stages, leveraging established technology and concepts. Geographic Information Systems (GIS) have historically enabled the storage, management, analysis, and visualisation of geographically referenced data (Philibert Petit, 2022). Traditional GIS mostly concentrated on static or intermittently updated data, producing snapshots of reality instead of continuous, real-time representations. Although GIS is robust for geographical analysis and mapping, it lacks the dynamic, bidirectional connection with the physical world that characterises a genuine digital twin.

The emergence of advanced sensor technologies, including LiDAR (Light Detection and Ranging), high-resolution satellite photography, and aerial photogrammetry, markedly improved the capacity to acquire detailed 3D spatial

data (Mahjoobi & Rafiei, 2024). This facilitated the development of more precise and lifelike virtual representations of edifices, infrastructure, and topography. These characteristics facilitated the development of increasingly immersive and intricate digital representations, transitioning from abstract maps to more concrete virtual landscapes.

The proliferation of pervasive connection via global navigation satellite systems (GNSS), mobile networks, and ultimately the Internet of Things (IoT), established the essential infrastructure for real-time data collection (Alonso et al., 2024; Azrour et al., 2024; Huang et al., 2023). Sensors may now transmit data continually from actual assets and environments directly into digital models. This ongoing data stream converted static GIS layers into dynamic, vibrant representations. A digital model of a bridge may receive real-time strain gauge data to indicate its structural integrity, or a city model could assimilate real-time traffic flow information. In addition, the concept of DTs has moved from the simple replication of physical components towards the modelling of processes and behaviours. Environmental models (such as air quality or noise pollution), infrastructure network simulations (such as water, power or communication) and human activity patterns are increasingly being incorporated into geospatial digital twins (Choi & Yoon, 2025; Hyre et al., 2022). This facilitates predictive simulations, such as modelling the effects of urban development on microclimates or projecting disease transmission within an urban area.

The advancement of intuitive interfaces and visualisation techniques, frequently utilising virtual reality (VR) and augmented reality (AR), has rendered geographic digital twins more accessible and engaging (Hyre et al., 2022). Urban planners, emergency responders, and asset managers may now engage with a virtual city, analysing scenarios and making informed decisions based on a comprehensive, real-time depiction of their surroundings. The shift towards interactive and intuitive platforms is essential for optimising the utility of geographic digital twins in many applications.

2.1.4 Challenges and Future Directions in Geospatial Digital Twins

Despite substantial advancements, the development and extensive implementation of geographic digital twins encounter numerous technical and practical constraints. To create and maintain high-fidelity digital twins across large geographic areas, such as entire cities or regions, requires significant

computational resources to acquire, process, store, and update data in real-time.(Attaran & Celik, 2023; Boccardo et al., 2024a; Weil et al., 2023). The scale, in terms of volume, velocity and variety, of geospatial data, remains an challenging task to manage.

Data privacy and security is a serious problem especially with personal location data or critical infrastructure information (M. E. Ali et al., 2024; Javed et al., 2022). It is important to develop strong cybersecurity standards and follow data protection legislation to foster trust and ethical use of geographic digital twins. Another problem is the merging of data from many sources and systems (David et al., 2025). Geospatial data is generally available in several formats and standards, making it difficult to be smoothly merged into a uniform digital twin platform (David et al., 2025). This points to a need for standard data models and open protocols that would allow the diverse pieces of a digital twin to communicate with each other successfully. Real-time communication for geographic digital twins in high demand Ultra low latency and high bandwidth networks are essential for fast response time applications such as autonomous car navigation or real time catastrophe management. This highlights the need for improvements in network infrastructure (5G and the future 6G) to allow for the smooth large-scale data transfer required for dynamic geographic digital twins.

There are several significant areas that will impact the emergence of geographic digital twins. Data models need to better capture the intricacies of physical settings and the processes of change within them. This includes the development of semantic models that characterises not just the shape of the spatial entities but also their semantics and relations. A digital twin of a building will not only be a representation of its physical form, but it will grasp its position in the wider urban system. Comprehensive security frameworks will be essential to safeguard sensitive geospatial data and maintain the integrity of digital twin operations. The use of blockchain and distributed ledger technology may provide effective solutions for secure data management and verifiable data trails in geographic digital twin ecosystems.

Interdisciplinary collaboration is essential for optimising the capabilities of geographic digital twins(Koldasbayeva et al., 2024a; Y. Li & Feng, 2025a). This requires a collaboration of urban planners, architects, engineers, computer scientists, environmental researchers, and policy makers. Each discipline offers distinct insights and prerequisites, necessitating a collaborative approach to

develop comprehensive and effective geographic digital twin solutions that tackle real-world difficulties.

Furthermore, the use of advanced technology will continue to be a driver for innovation. Edge computing enables the localised processing of geospatial data, thus reducing latency and bandwidth requirements for real-time applications. The future quantum computing may offer unique opportunities to model complex urban systems and optimise the distribution of resources between geospatial digital twins. Generation of synthetic environments or augmentation of visualisations with generative AI will become more and more relevant. The ethical and regulatory issues will be more prominent as geography's digital twins evolve and grow. Issues of data privacy, algorithmic bias in predictive analytics and the societal implications of pervasive surveillance all require careful consideration and regulation. Originally introduced in the context of product lifecycle management and subsequently applied to aerospace, the digital twin concept has emerged as a key and disruptive tool in the geospatial domain. The geospatial digital twin is a huge step forward in our capacity to understand, govern and improve our built and natural environments. The geospatial digital twin has evolved from its philosophical origins to become what it is today, an agile, data-driven model of the real world.

Geospatial digital twins, founded on GIS principles and augmented by developments in sensor technology, real-time data streaming, artificial intelligence, and detailed 3D modelling, offer unparalleled insights for urban planning, infrastructure management, environmental monitoring, and disaster response (Ba et al., 2025; Hananto et al., 2024; Tokyo Metropolitan Government Digital Twin Project, 2024; D. Wu et al., 2025). Despite the persistent issues of scalability, data privacy, interoperability, and real-time communication, continuous research and technical progress are addressing these constraints. The future of geographic digital twins is set for advancement, propelled by refined data models, fortified security frameworks, augmented interdisciplinary collaboration, and the incorporation of upcoming technology. As these virtual representations advance and gain widespread acceptance, they will assume an increasingly vital role in the development of intelligent, resilient, and sustainable cities and regions worldwide.

2.2 Digital Twins for built up environments : Urban Digital Twins (UDTs)

The concept of a "digital twin" has expanded significantly, from its origins in product lifecycle management to a potent tool for complex systems such as urban environments. In recent years, the concept of Urban Digital Twins (UDTs) has gained popularity, particularly in the geospatial setting. UDTs are virtual replicas of a city or a portion of it that are constantly updated with real-time data, creating a dynamic and interactive platform for planning, management, and analysis (Crampen et al., 2024). This literature study will look at the origins and evolution of the UDT idea, as well as its numerous applications and implementations in the built environment and will emphasize the critical role that geospatial information plays in its development.

2.2.1 Origins and Evolution of Urban Digital Twins

Originally, digital twins were static 3D models with some related data. However, as computing power increased and sensor technology became more sophisticated and cost-effective, the concept evolved. This transition was enabled by the Internet of Things (IoT) that provided a continuous flow of real-time data from physical assets to their digital twins (Allam et al., 2022; Boltsi et al., 2025). The ever-growing data streams have turned digital twins from static representations into dynamic models that can provide accurate reflections of current conditions and predict future behaviour. The incorporation of artificial intelligence (AI) and machine learning (ML) algorithms within the digital twin framework enhanced analytical skills, pattern identification and predictive modelling (Cina et al., 2025; Onma Enyejo et al., 2024). The operation of the digital twins was critically dependent on data collection, analysis, and feedback loops. It helps to make better decisions and improve results. Urban Digital Twins (UDTs) are the digital twin implementation at the urban scale. Cities are complex social interactions, sophisticated infrastructural systems, and large data volumes, making them a desirable, but difficult subject for this technology. The built environment is inherently complex and dynamic. This covers buildings individually and whole cities. To properly manage and plan these settings, one must have a thorough understanding of the various components and their relationships. UDTs are proposed as a promising candidate to address this complexity and provide a unified platform for the integration of heterogeneous urban data and execution of holistic analyses. The shift from industrial systems to UDTs has resulted in a

major increase in complexity and data volume. A metropolis, on the other hand, consists of millions of interconnected assets, processes, and people, unlike a single aeroplane engine or a single piece of industrial equipment. UDTs demand a solid data architecture, complex modelling approaches and robust analytical tools. The motivation to develop UDTs is diverse, and stems from the increasing challenges of rapid urbanisation, climate change, resource depletion and the need for more efficient and sustainable urban living. UDTs offer to give urban planners, policymakers, and residents unique insights into how cities work, allowing for better informed decision-making and collaborative governance.

2.2.2 Geospatial Context: The Foundation of UDTs

The "geospatial context" is not an afterthought, but rather a fundamental and distinguishing feature of UDTs. Cities exist in space, and almost all urban data includes a geographic component. Geospatial information systems (GIS) and related technologies serve as the foundation for UDTs. Geospatial data offers the basis for organising, visualising, and analysing urban phenomena within a UDT, ranging from the precise position of infrastructure pieces to the geographical distribution of population density (Argota Sánchez-Vaquerizo, 2025; Diaz-Sarachaga, 2024). Without a strong geographic foundation, a UDT is nothing more than a collection of disconnected data points.

The development of UDTs is based on geospatial technologies. Firstly, they offer the correct capturing and representation of a city's physical environment in three dimensions. This includes detailed representations of buildings, roads, landscaped areas and subsurface utilities. Accurate geographical datasets require LiDAR (Light Detection and Ranging), photogrammetry and satellite imagery. Secondly, GIS provides sophisticated tools for integrating and handling different types of georeferenced materials. This allows a UDT to aggregate data from disparate sources, such as sensor networks, traffic cameras, utility meters and social media feeds, to a common geography. Third, geospatial analytic capabilities allow UDTs to execute complex geographical queries, identify patterns, simulate spatial scenarios, and display results on a map interface. This is the key to understanding the spatial relationships and dependencies of the urban environment.

The development of geospatial technologies has resulted in the development of advanced 3D city modelling standards (e.g. CityGML), real-time location services and advanced spatial analytics platforms, which have directly contributed

to the creation of UDTs. These advances enable the development of UDTs that are both geometrically accurate and semantically rich, resulting in more intelligent and context-aware urban management.

2.2.3 Applications of Urban Digital Twins

The potential applications of UDTs are enormous, encompassing practically every facet of urban administration and planning. These virtual replicas provide a dynamic platform for investigating numerous "what-if" scenarios, optimizing resource allocation, and improving the quality of life for city dwellers. The variety of implementations reflects the versatility and maturation of UDT technology.

One of the most important applications is urban planning and development. UDTs provide planners an opportunity to visualise how future developments will appear in their real urban environment, evaluate the impact on the environment and test traffic flows or pedestrian movement prior to construction. This allows for early detection of potential problems and the development of more efficient and liveable urban environments. A UDT can be used to simulate the effect of a new skyscraper on the sunlight access of neighbouring buildings or its contribution to the urban heat island effect. This ability to predict reduces the risk and costs of urban development.

Another important issue is infrastructure management. UDTs are able to generate virtual models of utilities networks such as water, electricity, gas, telecommunications, transport systems such as roads, trains, and public transit and other public facilities (AlBalkhy et al., 2024; Botín-Sanabria et al., 2022; Eriksson & Harrie, 2021). City operators can monitor asset performance, discover abnormalities, estimate maintenance needs, and optimize operations by incorporating real-time sensor data. For example, a UDT can help detect a leak in a network of water pipes, predict traffic congestion or optimise energy consumption in a district. Such proactive infrastructure management means less downtime, lower operating costs and better service delivery.

UDTs also are helpful for sustainability and environmental management. Cities have huge issues around air quality, waste management and energy use. UDTs can integrate data from environmental sensors, meteorological stations and energy meters to provide a general insight on environmental performance of a city. It allows officials to predict the impact of different policy interventions – such as the introduction of electric vehicles or the expansion of green space – on

air quality and carbon emissions. UDTs are key in developing successful sustainability plans by modelling multiple scenarios. UDTs are critical to emergency response and disaster management. UDTs are able to combine real-time data with precise geographical models to forecast and simulate the impact of disaster scenarios (e.g., floods, earthquakes, fires) on urban infrastructure and population. This enables emergency services to develop better response plans, allocate resources more effectively and even direct evacuation efforts in real time. To be able to see the scenario play out in a virtual environment can greatly improve crisis coordination and decision making.

UDTs are also increasingly used in civic participation and participatory planning. UDTs can provide the citizens with a better sense of participation in urban planning processes, by making the complex urban data more accessible and understood through interactive 3D models. Residents can see planned changes to their neighborhoods, submit feedback, and understand the consequences of various development options. This promotes better transparency, increases confidence between citizens and municipal governments, and results in more inclusive urban development. Despite its enormous promise, the broad use of UDTs confronts numerous severe difficulties. These constraints must be solved so that UDTs can fully realize their transformational potential. Recent systematic reviews have highlighted major issues such as interoperability, data collection, data quality, modelling, and governance.

The data size of datasets required for an EDT development is very important. UDT requires massive data from different sources, often in different formats and standards. Interoperability and semantics across disparate information is crucial for a coherent and working digital twin. This requires standardised data models and data interchange protocols. Moreover, data acquisition and actuation can be complicated and costly, requiring large sensor networks and robust data pipelines. Quality and harmonisation of data is essential. Wrong data or insufficient data can result in wrong conclusions and decisions. The protection and security of data is a big issue, especially in the case of sensitive urban data. UDTs require a large amount of data and complex simulations, which call for a large infrastructure for data storage, processing, and networking. Advanced modelling, simulation, and decision-support tools are now being developed, with a need for more sophisticated algorithms capable of integrating and predicting the interconnections of multiple urban systems. Data visualization and information display are also critical for making UDTs accessible and interpretable to a wide variety of stakeholders.

Finally, there are substantial gatekeeping barriers of people, capital and organisational resources. Building and sustaining a UDT requires people trained in data science, urban planning, software development, and geospatial analysis. Successful uptake of UDT depends on sufficient funding and establishment of appropriate governance, organisational and societal structures. This includes the creation of unambiguous definitions of roles and responsibilities, legal frameworks for data interchange and use, and encouragement of collaboration between local ministries and stakeholders.

The future of UDTs could be characterised by spectacular accomplishments in many disciplines. More research on AI and machine learning will improve the predictive abilities of UDT. This will allow better prediction of urban patterns and behaviours of systems. Blockchain technology can address data security, transparency and trust challenges especially in multi-stakeholder environments. The development of open-source platforms and standard APIs would increase interoperability and lower the barriers to entry for cities wanting to implement UDTs. Finally, a more robust socio-technical R&D agenda will be key to ensuring that UDTs are not only technological wonders, but tools that truly meet the needs of urban residents and help build more resilient and sustainable communities. The further development of UDTs has been driven by technological innovation and a profound respect for the subtleties of urban life, and they have the potential to radically change how we plan, manage and engage with our built environments.

2.3 Energy Digital Twins : What, why and how ?

The concept of “digital twin” technology, virtual replica of a physical asset, process, or system, has gained immense significance in a wide range of fields. In the context of geospatial applications of energy systems in built environments, it creates a “Energy Digital Twin”. This sophisticated approach offers huge opportunities to enhance energy efficiency, optimise resource management and foster sustainable urban development. This literature review will discuss the key elements of Energy Digital Twins, i.e., what are they, why do we need them? and how can they be implemented in built-up environments? with an emphasis on the role of geospatial data.

2.3.1 Defining the Energy Digital Twin in Built Environments

An Energy Digital Twin for Built Environments can be defined as a dynamic, virtual depiction of the energy characteristics of a physical structure, campus, or even an entire city. This digital twin is fed real-time data streams from sensors, building management systems and other sources, creating a living model that mirrors the actual energy performance and conditions of its physical twin. A digital twin is not merely a static building information model (BIM) but is linked to the physical environment in two ways, where data flows and interactions can take place. This synchronisation in real time enables the digital twin to mirror the operational states with accuracy, forecast future behaviours, and take informed decisions.

Within urban energy systems, a digital twin can be applied to model building energy consumption under varying weather conditions, occupancy patterns, or construction strategies. The predictive ability of digital twins helps with informed decision-making and sustainable planning for a wide range of implementation areas. And analytics on the digital twin can provide useful insights, detect anomalies, and recommend proactive maintenance or policy interventions. Table 2 summarises the key elements for assessing reproducibility in Geospatial Digital Twins, including a brief description of each element and examples of technologies or dataset resources that can support their effective implementation across different disciplines.

Table 2: Key Elements of Energy Digital Twins and Relevant Geospatial Technologies, information from (Battye & Perinpanayagam, 2025; Cespedes-Cubides & Jradi, 2024; Koirala et al., 2024b)

Element	Description	Technologies & Dataset Resources (possibilities)
Physical Assets	Real-world entities needing replication	LiDAR, Photogrammetry, Remote Sensing
Virtual Models	Digital replicas with spatial and temporal attributes	GIS, BIM, 3D Modelling Software
Data Flows	Connectivity between physical and digital	IoT, Edge Computing, Cloud Integration
Predictions, Analytics and Simulations	Forecast outcomes, simulate system behaviours and test “what if” scenarios	Machine learning models, climate models, Building energy models

The digital twin for the energy sector is comprised of several layers of information. It contains information about energy generation (e.g. solar panels), consumption (e.g. HVAC systems, lighting, occupant behaviour), storage (e.g. batteries) and distribution networks. It also takes into account environmental factors such as temperature, humidity and sun radiation, which is a major factor in energy efficiency. By adding geospatial context, this digital representation becomes geographically explicit, connecting energy data and models to a specific place in a building or urban setting. This enables spatial study of energy patterns, the discovery of energy hotspots or cold spots, and the optimization of energy flows between geographically dispersed assets. A digital twin, for example, may measure the energy consumption of individual apartments in a multi-story structure or monitor the energy production of solar installations throughout an entire city block, all while visualizing it in a spatially realistic digital environment.

2.3.2 The Imperative for Energy Digital Twins: Why Built Environments Need Them

The importance to implement Energy Digital Twins stems from several interconnected global and local concerns, most notably rising energy demand, the compelling need to combat climate change, and the pursuit of operational efficiencies. Buildings are major energy users and contributors to greenhouse gas emissions. In the European Union, for example, buildings consume roughly 40% of total energy. This indicates a large scope for improvement in the operational and maintenance phases of the structures. One of the key drivers for the use of Energy Digital Twins is the potential to improve energy efficiency. Digital twins can be used to constantly monitor and analyse energy consumption, identifying inefficiencies, detecting overuse and developing optimisation measures. This real-time feedback mechanism allows operators to optimise building systems such as HVAC, lighting and electricity distribution, reducing waste and improving overall performance.

According to studies, implementing a digital twin can save up to 30% on energy. For example, a digital twin can simulate various operational situations, such as altering thermostat settings or optimizing ventilation cycles depending on projected occupancy, to determine the most energy-efficient configuration while maintaining occupant comfort. Beyond mere efficiency, Energy Digital Twins help to reduce operational costs. They reduce unexpected malfunctions and increase equipment lifespan by optimizing energy use and enable predictive

maintenance. One of the biggest benefits of digital twins is predictive maintenance. Digital twins use analytics models and real-time data to predict when equipment might fail before it actually fails. This transformation turns maintenance into a proactive and planned activity rather than a reactive and expensive activity, dramatically reducing repair costs and downtime. With the use of a digital twin's performance data, a failing HVAC component can be identified and replaced during scheduled maintenance without waiting for an entire system failure during high demand. Energy Digital Twins also help considerably in sustainability endeavours and in the protection of the environment. They help to reduce the carbon footprint of the built environment by optimising the use of energy and by better integrating renewable energy sources. This aligns with the global trend towards net-zero emissions and climate-responsive municipal plans. For example, a digital twin can simulate what would happen if solar panels or wind turbines were installed onto a building's energy system to decide the optimal number and position to maximise renewable energy generation whilst minimising environmental impact. In the context of smart cities, digital twins allow to achieve large sustainability goals by enabling the integration of zero-energy buildings (ZEBs) and the optimisation of the energy distribution in urban grids. The complexity of modern building systems, together with the increasing volume of data they generate, need sophisticated management solutions. Traditional techniques frequently fail to address the complex interdependences between various building components and external environmental conditions. Energy Digital Twins offer a comprehensive perspective by combining various data sources into a single platform for detailed analysis and control. This provides better decision-making, increased occupant comfort, and more robust energy infrastructure.

2.3.3 Use case of Energy Digital Twins in Built Environments: Concepts and Methodologies

The implementation of Energy Digital Twins in built environments is a complicated process that includes multiple essential stages, including as data collecting and modelling, analysis, visualization, and continuous maintenance. The success of an Energy Digital Twin is strongly reliant on a strong framework that integrates diverse technologies and processes, especially in a geographic setting.

2.3.3.1 Data Acquisition and Integration

The foundation of the development of any use case of a digital twin is data. For an Energy Digital Twin in a built environment, this involves collecting a wide array of dataset and associated information from diverse sources. This includes:

- **Geospatial Data:** Location-specific information, including building footprints, 3D models of structures, urban planning data, elevation models, and infrastructure layouts can be derived from the advanced geospatial datasets like point clouds.
- **Sensor Data:** Real-time data from IoT sensors monitoring temperature, humidity, CO2 levels, light intensity, occupancy, and energy consumption of various appliances and systems.
- **Building Management Systems (BMS) Data:** Historical and real-time operational data from HVAC, lighting, security, and other automated building systems.
- **External Data:** Weather forecasts, energy prices, grid load data, and even social media sentiment related to building comfort can be integrated in an EDT to provide a more comprehensive perspective.
- **Building Information Modeling (BIM) Data:** BIM provides a rich, static, geometric, and semantic dataset that forms an excellent starting point for building a digital twin. It offers detailed information about building materials, components, and systems, which can be enriched with real-time operational data.

Integrating these disparate data sources is a significant challenge, requiring standardized protocols and robust data infrastructures. Data normalization, cleansing, and secure transmission are critical to ensure the accuracy and reliability of the digital twin.

2.3.3.2 Modeling and Simulation

Once data is acquired, it's used to build and continuously update the digital model. This involves creating a virtual replica that accurately represents the physical energy system. Key modeling techniques include:

- **3D Geospatial Models:** These models provide the visual and spatial context, allowing for the visualization of energy performance data directly on a

geographically accurate representation of the built environment. This enables spatial analysis, such as identifying areas with high solar gain or poor insulation. Urban-scale digital twins can visualize energy consumption across multiple buildings, helping city planners make informed decisions about infrastructure development.

- **Physics-based Models:** These models use fundamental laws of physics (e.g., thermodynamics, fluid dynamics) to simulate the behavior of building components and energy flows. They provide a high degree of accuracy for predicting performance.
- **Data-driven Models:** Leveraging machine learning and artificial intelligence, these models learn patterns from historical and real-time data to predict future energy consumption, identify anomalies, and optimize system operations. For example, AI can be used to predict energy demand based on weather forecasts and historical usage patterns.

2.3.3.3 Analysis and Visualization

The strength of an Energy Digital Twin lies in its ability to analyze complex data and present actionable insights through the means of visualisation. This involves:

- **Real-time Monitoring:** Continuously tracking key energy performance indicators (KPIs) and displaying them through intuitive dashboards.
- **Predictive Analytics:** Using models to forecast future energy demand, identify potential equipment failures, and predict the impact of various operational strategies.
- **Scenario Planning and Optimization:** Simulating different scenarios to evaluate the impact of changes (e.g., upgrading insulation, installing new equipment, altering operational schedules) before implementing them in the physical world.
- **Anomaly Detection:** Automatically identifying unusual energy consumption patterns that might indicate equipment malfunction, leaks, or inefficient operation.
- **Geospatial Visualization:** Presenting energy data and analytical insights spatially such as heat maps showing energy intensity across a district.

2.3.3.4 Interoperability and Feedback Loop

A real digital twin provides a continuous and bidirectional feedback loop to its physical counterpart. The insights received from the digital twin can be used to regulate or change physical systems in the built environment. This necessitates strong communication protocols and interoperability between the digital twin platform and other building control systems. For example, the digital twin may recommend altering a chiller's setpoint, which can then be relayed straight to the BMS for implementation.

2.3.4 Implementations of Energy Digital Twins in Built Environments

Energy Digital Twins' adaptability enables a wide range of applications at different scales within built environments, from individual buildings to entire urban districts. Their implementations are changing the way energy is managed, consumed, and integrated, especially when viewed from a geographic perspective.

2.3.4.1 Building-Level Optimization

At the individual building level, Energy Digital Twins are primarily employed for detailed energy performance monitoring and optimization.

- **Predictive HVAC Control:** By combining real-time indoor climate data with external weather forecasts and occupancy predictions, a digital twin can dynamically adjust HVAC setpoints and airflow rates to maintain comfort while minimizing energy consumption.
- **Lighting Management:** Digital twins can optimize lighting schedules and intensity based on natural daylight availability, occupancy, and user preferences, integrating with automated shading systems to maximize daylight harvesting and reduce artificial lighting needs.
- **Sub-metering and Anomaly Detection:** Digital twins can integrate data from various sub-meters to identify specific areas or equipment that are consuming excessive energy. Anomalies, such as unusual spikes in power draw, can be flagged immediately, indicating potential equipment malfunction or energy wastage.
- **Retrofit Planning and Simulation:** Before undertaking costly energy efficiency retrofits (e.g., insulation upgrades, window replacements), a digital twin can simulate the potential energy savings and return on investment, helping

building owners make informed decisions. This allows for spatial analysis of how different retrofit strategies might impact different parts of the building.

2.3.4.2 Urban-Scale and Smart City Integration

At the urban level, Energy Digital Twins are central to smart city initiatives aimed at creating more sustainable and resilient urban environments.

- **Urban Energy Planning:** City planners can use urban-scale digital twins to analyze energy consumption patterns across different neighborhoods, identify areas with high energy intensity, and inform decisions about urban development, infrastructure planning, and the deployment of renewable energy sources.
- **Zero-Energy Building (ZEB) Integration:** Digital twins facilitate the integration of ZEBs into smart city frameworks by monitoring their energy performance and ensuring they contribute to the overall energy balance of the urban area.
- **District Heating and Cooling Optimization:** For cities with district heating or cooling networks, digital twins can optimize the entire system, from energy generation plants to distribution networks and building demand.
- **Resilience and Emergency Management:** In the event of power outages or other disruptions, an urban energy digital twin can provide real-time situational awareness, identify critical infrastructure, and simulate recovery scenarios to restore energy services efficiently.
- **Policy and Regulatory Support:** By providing granular data and insights into urban energy performance, digital twins can inform the development of more effective energy policies and regulations, promoting sustainable urban growth.

Further research in the field of EDTs, collaboration, and funding are required to realise broad adoption of their applicability in built environments. However, their enormous potential for energy saving, cost reduction and environmental sustainability makes them a key technology for the future of urban development. The Energy Digital Twin is a new approach to energy management in built environment. It moves beyond the static, traditional models by creating dynamic, real-time virtual representations of physical energy systems, providing an unmatched depth of knowledge and control. This literature study has focused on the key concept of an Energy Digital Twin, highlighting its continuous data

stream and bidirectional link with the physical world, supported by essential geographical context that enables location-aware analysis and optimisation. It is adopted for good reasons; the urgent need to combat climate change through a major increase in energy efficiency, the desire to decrease the rising operational costs of building management, and the need for sustainable urban development. Energy Digital Twins provide a powerful solution to these challenges through continuous monitoring, predictive maintenance and operational optimisation. Their application leads to considerable energy savings and operating cost reductions, as repeatedly demonstrated in studies.

Adopting Energy Digital Twins “how” is complex interplay of data collection from multiple sources, sensors, BMS and most importantly diverse geographical datasets followed by advanced modelling and simulation tools. These models, whether physics-based, data-driven or 3D geospatial visualisations, convert raw data into useful information. The resulting analysis and visualisation provide stakeholders with the tools needed to make informed decisions, optimise systems, and plan for future interventions. Although challenges such as high upfront costs, data integration issues, and the need for standardisation remain, they are being addressed through ongoing research and technological advancements.

The scope of application of Energy Digital Twins is wide, from optimising HVAC and lighting systems in single buildings, to managing complex microgrids in campuses and supporting strategic energy planning of entire smart cities. In both cases, the geospatial dimension is an element of key importance that allows the energy performance knowledge to be accurately known in its real spatial context. As built environments evolve and the need for sustainable solutions increases, Energy Digital Twins will surely continue to be at the forefront, serving as a critical tool for achieving energy efficiency, resilience and operational excellence in tomorrow’s urban infrastructure.

2.3.4.3 Challenges in Implementation of EDTs

Despite the significant benefits, implementing Energy Digital Twins, especially in existing buildings, presents several challenges:

- **High Upfront Cost:** Sensors, data infrastructure, software and specialised expertise can be expensive.
- **Data Integration Complexity:** Challenges can arise when integrating data from different, often proprietary, systems.

- **Lack of Standardisation:** Absence of common standards for data formats and communication protocols hinders interoperability.
- **Scalability:** Building robust and scalable architectures is crucial for scaling digital twin solutions from individual buildings to entire campuses or urban areas.
- **Legacy Systems:** Older buildings generally don't have the digital infrastructure needed to allow for seamless data acquisition, making it a complex and costly retrofitting process.
- **Security and Privacy:** Protecting sensitive energy consumption data and securing connected systems are critical concerns.

Addressing these issues will require collaboration between technology providers, lawmakers, building owners and researchers to develop standardised procedures, reduce implementation costs and improve cybersecurity. Incremental developing, starting with small test projects and expanding incrementally, can also help to manage the complexity and cost of implementation.

2.4 Geospatial datasets for EDT development

The development of reliable Energy Digital Twins for buildings and urban environments depends on the precise extraction, structuring, and integration of geometric features derived from geospatial datasets. These datasets include LiDAR point clouds, photogrammetric images, multispectral and thermal data, GIS layers, and 3D models that capture shape, topology, and physical properties of the built environment. The precision and comprehensiveness of these data directly decide the performance of digital replicas in building energy assessment, thermal behaviour simulation, urban-scale energy planning, and continuous monitoring of the building performance. The rapid development of high-resolution sensing technologies, including UAV borne sensors, terrestrial laser scanners, mobile mapping systems and advanced image-based reconstruction workflows has significantly increased the scope of geometric information that can be acquired. Simultaneously, researchers are still confronted with traditional challenges, such as data interoperability, occlusions, sensor noise, complex architectural features, and multi-source data fusion.

This review summarises progress in geospatial data acquisition, geometric reconstruction and feature extraction that are currently shaping the state of the art in Energy Digital Twin development. It discusses the strengths and weaknesses of key datasets and processing techniques, the transition from single data source to

multi-sensor work streams and the growing convergence of building information modelling and GIS platforms. It also discusses how geometric features extracted from point clouds and imagery are converted to structured models such as CityGML, IFC and custom semantic frameworks, to support simulation-ready energy analysis.

2.4.1 Geospatial Data Sources for Geometric Reconstruction

2.4.1.1 LiDAR point clouds

LiDAR point clouds remain one of the most widely used datasets for building geometry reconstruction due to their accurate range measurements, high sampling density, and ability to penetrate vegetation under favorable conditions. Both terrestrial and aerial LiDAR provide reliable geometric details essential for roof extraction, façade profiles, window locations, and structural outlines. The quality of the surface geometry is especially important for Energy Digital Twins, as it directly impacts thermal simulations, daylighting computations and airflow modelling. And this is why LiDAR is so important. Recent research has shown great progress on LiDAR-based urban and campus reconstruction by fusing UAV-mounted sensors. For instance, a university campus 3D model was generated using a combined UAV photogrammetry and LiDAR workflow, which resulted in a high-fidelity model with good geometrical consistency, point spacing near 5 cm, and better façade completeness by using oblique flight paths. These results show the growing importance of UAV-LiDAR for detailed large-scale urban mapping, where building energy simulations require accurate roof structures, shading geometries and surface orientations.

2.4.1.2 Photogrammetric datasets

Photogrammetry derived from multi-view RGB imagery complements LiDAR by providing dense point clouds, textured meshes, and visually rich models. While LiDAR excels in geometric precision, photogrammetry enhances visual realism and supports semantic interpretation of materials, façade elements, and contextual surroundings. The availability of low-cost UAV platforms has made photogrammetric methods a common practice for the capture of façades and also roof structures. It has been shown that the combination of photogrammetric imagery and LiDAR can reduce the geometric deviations and improve the overall accuracy of the model. A recent workflow combining nadir and oblique photographs has shown to be able to reduce the surface deviation by 30%

compared to the use of only nadir imagery, stressing the importance of multi-angle data acquisition for the generation of building surfaces that are not visible from overhead flight configurations. Such improvements are important for Energy Digital Twin applications where uncertainties in surface geometry lead to errors in heat transfer modelling and shadow studies.

2.4.1.3 Thermal point clouds and thermal imagery

Thermal datasets are increasingly recognized as valuable sources for Energy Digital Twin development because they directly measure surface temperature, one of the most important variables for building energy performance. Thermal imaging has been used for qualitative inspection in the past, but recent research has been directed towards embedding thermal measurements in point clouds and BIM-GIS structures. A workflow was presented for the integration of thermal point clouds into BIM and GIS platforms showing procedures to represent temperature attributes as native properties of building elements frontiersin.org. Thermal data that is structured and interoperable can then be used for thermal simulations, anomaly detection and energy diagnostics instead of isolated images. Thermal point clouds also show promise for envelope performance analysis, detecting infiltration, and assessing insulation. The acquisition of temporal thermal datasets allows for dynamic monitoring and integration into real-time Energy Digital Twins, as thermal conditions depend on environmental factors. Challenges persist with sensor noise, emissivity changes across materials and alignment of thermal scans with geometric models. The increasing importance of multi-layer digital twins implies that thermal datasets will become important as an additional layer of information to geometric data.

2.4.1.4 GIS layers and topographic sources

GIS datasets provide large-scale contextual information needed for urban-energy simulations, including parcel boundaries, land-use layers, transportation networks, and topographic models. Many cities maintain GIS inventories of building footprints, height attributes, roof types, and utility networks. These datasets are usually used for initialising building geometry or validating reconstructed models. GIS layers, as a rule, do not contain detailed 3D information, but they are necessary for creating geospatial relationships, coordinate system correlation, and georeferencing point clouds or imagery in a spatial reference network. GIS also allows to integrate attributes like land cover and zoning information needed for district level energy simulation and microclimate analysis. The integration of

thermal and 3D datasets into GIS structures, as demonstrated in the thermal point cloud workflow validated in ArcGIS Pro frontiersin.org, indicates the growing ability of GIS environments to host multi-sensor information for energy modelling.

2.4.1.5 LiDAR–photogrammetry fusion

The generation of Energy Digital Twins (EDTs) is increasingly based on the fusion of various geospatial datasets to overcome the limitations of individual datasets. Multi-source integration gives completeness, accuracy and semantic richness. LiDAR gives you good depth data, photogrammetry gives you nice textures and colour. The approach deals with common problems like photogrammetric noise and the coarse textural detail of LiDAR. This is a representative example of the UAV campus mapping workflow, where LiDAR scans were co-registered with photogrammetric reconstructions into a common coordinate system, enhancing edge sharpness and reducing surface deviation. This data fusion helps create simulation-ready surfaces that correctly represent material boundaries, slopes and façade openings for energy modelling.

2.4.1.6 Thermal–geometric integration

Thermal datasets must align with geometric models to be useful for energy diagnostics. The BIM-GIS integration of thermal point clouds shows how assigning average surface temperatures as native attributes to building components enables the formation of multi-layer digital twins frontiersin.org. The main challenge lies in correctly registering thermal data with 3D models and accounting for emissivity and environmental variations.

For Energy Digital Twins, thermal integration supports tasks such as:

- identifying insulation failures
- detecting heat leaks
- validating simulation outputs
- calibrating building performance models

2.4.1.7 GIS–BIM interoperability

The integration of GIS and BIM is essential for linking detailed building geometry with urban-scale context. However, differences in schemas, coordinate systems,

and attribute definitions complicate interoperability. Recent approaches create workflows for exporting data between BIM formats such as IFC and GIS environments, enabling thermal point clouds and other properties to be embedded within BIM structures frontiersin.org.

GIS-BIM integration supports Energy Digital Twins by allowing:

- shared spatial referencing
- hierarchical relationships between buildings and districts
- consistent attribute structures for simulation models
- coordinated maintenance of geometric and semantic data

2.4.1.8 Image-assisted 3D reconstruction

Recent reviews on geometric digital twins emphasize the role of images as complementary input for detecting transparent or specular surfaces, which are problematic for LiDAR alone. Images help resolve ambiguities in façade geometry, window delineation, and material boundaries. Deep learning methods applied to RGB images enable semantic classification that can be integrated with geometric data for improved segmentation.

2.5 Feature extraction from the geospatial datasets

Accurate extraction of building features from geospatial datasets (GIS layers, point clouds, 3D models etc.) is a crucial step in the reconstruction of building geometry for applications such as Building Information Modeling (BIM), urban simulation, energy modeling, and heritage documentation. With the increasing availability of high-density LiDAR and photogrammetric data, several methods have been proposed, each addressing the challenges of data occlusion, noise, and variability in architectural styles.

2.5.1 Geometric feature-based methods

Early approaches to window detection relied heavily on geometric properties of point clouds, assuming rectilinear, planar, and repetitive features typical of windows. (Lafarge & Mallet, 2012) used a probabilistic model for facade decomposition, integrating line and plane detection for semantic segmentation. Similarly, (Pu & Vosselman, 2009) proposed a RANSAC-based technique to fit planar surfaces, followed by segmentation of voids and recessed regions as

candidate windows. However, such methods struggle with incomplete data due to occlusions (e.g., trees or balconies) and often require significant parameter tuning. Their reliance on explicit shape assumptions also limits generalizability to varied architectural styles.

2.5.2 Image-feature based methods

Several studies have used orthographic projections of point clouds to produce facade images (depth or intensity maps) which allow the application of 2D computer vision techniques. (Becker & Haala, 2009) applied morphological filters to find window patterns on projected elevation maps. The method takes advantage of the strong 2D pattern recognition and reduces the computational complexity. To improve the detection in sparse areas, (Albano, 2019; Guo et al., 2021) proposed a method of point cloud projection combined with feature matching based on SIFT between image data and point cloud data. However, information can be lost with projection methods, especially for very irregular facades or with oblique viewpoints.

2.5.3 Template matching and symmetry-based methods

Exploiting the repetitive nature of architectural elements, several researchers introduced template matching and symmetry analysis. The procedure with the Markov Random Fields (MRF) and symmetry constraints was also employed to identify window candidates on building façades. (Zeng et al., 2013) proposed a pattern-recognition-based model where templates of typical windows were matched to projected façade data. These techniques work well in modern urban environments where repetition is prevalent but perform poorly in older or non-standardized buildings with varied window designs.

2.5.4 Deep learning and semantics-based methods

Deep learning has been successfully applied to semantic segmentation of point clouds. PointNet (Qi, 2017) and its variants enable end-to-end classification of 3D points, including façade elements such as windows. More recent approaches such as KPConv (Thomas, 2019) and (L. Chen, 2019) have improved this by learning local geometrical features from unstructured data. (N. Wang et al., 2024; J. Zhang et al., 2022) proposed a façade-specific network trained on labelled urban datasets for detecting windows with high precision, outperforming classical methods under challenging lighting and occlusions. However, these models need large, labelled

datasets for training, and often do not generalise across cities and architectural types without domain adaptation.

2.5.5 Hybrid or Integrated approaches

Hybrid methods are a mixture of geometric, image-based and learning-based methods. The geometric segmentation based approaches have combined 2D CNNs on image projections with 3D post-processing to re-project the labels back to the original point cloud. These approaches aim at leveraging the merits of multiple techniques to strike a balance between accuracy and robustness. However, the computational overhead and the system complexity are still major limitations. Even with progress there are many difficulties. Detection of windows is obstructed by occlusions (vegetation, balconies), variable window geometry and noise in the point clouds. Most existing methods are sensitive to data resolution and lack automation for different urban scenarios. Also, there is no common benchmark dataset for evaluation of window extraction methods leading to inconsistent comparisons in the literature. Future work may include self-supervised learning for reducing the cost of data labelling, transfer learning for cross-city adaptation, and integration with GIS and BIM platforms for enriched semantic modelling.

2.5.6 Feature-based Methods

2.5.6.1 Building footprint and boundary delineation

One of the earliest steps in building geometry reconstruction is extracting building footprints from point clouds or aerial imagery. Classical methods rely on filtering ground-level points, clustering elevated points, and projecting them onto a horizontal plane. More advanced approaches use segmentation techniques or machine learning to classify roof points and refine building outlines. Automatic footprint extraction continues to face challenges when architectural complexity, vegetation cover, or shadowing distort elevation measurements. Nonetheless, the combination of LiDAR and photogrammetry significantly improves boundary delineation because height and texture cues complement one another. Footprints derived from such combined datasets serve as core references for assembling 3D building layers and building simulation-ready models.

2.5.6.2 Roof structure reconstruction

Roof shape is a strong component of building energy performance as it determines solar exposure, heat gains and ventilation potential. Roof reconstruction techniques typically utilise plane detection from point clouds, clustering of roof surfaces, and classification of roof types (e.g., gabled, hip, or flat roofs). Techniques include RANSAC based plane extraction, Hough transform approaches, region growing and deep learning for roof semantic segmentation. While LiDAR is generally better at capturing the geometry of the roof due to its direct measurement capabilities, photogrammetry provides complementary textural information for better surface segmentation. The UAV study with nadir and oblique imagery showed improved roof and facade completeness and showed multi-view photogrammetry as a valuable addition to the roof reconstruction workflow. Roof geometry accuracy is critical for Energy Digital Twins to evaluate photovoltaic potential, solar exposure and thermal loads.

2.5.6.3 Façade reconstruction and opening detection

The façades consist primarily of windows, doors, shading devices and architectural details, which have a big influence on the thermal behaviour of the building. Reconstruction of façade geometry is a challenging task due to data occlusion by street-level obstacles, vegetation and limited observation angles. The paper discusses façade reconstruction approaches in detail and stresses the importance of combining terrestrial, aerial and mobile sensing systems to acquire façade elements from different viewpoints. The review mentions that detection of windows and doors is still challenging due to transparent and reflective surfaces, differences in façade materials and lighting conditions. Openings influence daylighting, heat transfer and ventilation. Energy models need to have an accurate size and placement of windows. Hence, methods based on deep learning, edge detection and shape priors are being actively investigated to improve extraction of façade components.

2.5.6.4 Indoor geometry reconstruction

Indoor environments are complex due to narrow corridors, occlusions, furniture, and reflective surfaces. Accurate indoor geometry is essential for HVAC simulation, thermal zoning, and indoor comfort modeling. Methods for indoor

reconstruction include SLAM-based mobile mapping, terrestrial LiDAR scanning, and image-assisted point cloud segmentation.

Recent advances emphasize multi-sensor integration and geometric reasoning for improving indoor model reliability. A study focusing on indoor reconstruction from point clouds highlights challenges in clutter removal, surface classification, and room boundary detection, and discusses the need for more robust segmentation strategies. Indoor modeling remains one of the most difficult components of Energy Digital Twins because even small geometric inaccuracies can propagate into large energy simulation deviations.

2.5.7 Feature Modeling for Energy Digital Twins

Geometric features extracted from geospatial datasets must be converted into structured representations that support computational analysis.

2.5.7.1 Parametric and semantic building models

Energy simulations require parametric models that define surfaces, volumes, material properties, and boundary conditions. Semantic structures such as CityGML and IFC are important because they incorporate building component hierarchies and relationships. Increasingly, workflows convert point cloud or image-based reconstructions into these semantic formats. One of the recent reviews proposes a new geometry-based object hierarchy for improving the construction and maintenance of geometric digital twins, focusing on object classes that are most essential and frequently used. Such hierarchies simplify energy model creation because they emphasize geometric properties over functional labels, ensuring surfaces are organized in a manner that supports computational modeling.

2.5.7.2 Extraction of thermal, radiative, and material properties

Beyond geometry, Energy Digital Twins require surface properties that influence heat transfer and energy flows. While some properties can be derived from GIS or BIM attributes, others must be inferred from imagery or estimated using machine learning. For example:

- thermal datasets provide surface temperature measurements
- multispectral imagery contributes material classification

- LiDAR intensity can serve as a proxy for reflectance

The embedded thermal-point-cloud approach demonstrates a structured workflow in which thermal data becomes part of the building's digital representation rather than an external dataset frontiersin.org. Linking such attributes with geometric surfaces allows simulation engines to rely on real measurements for calibration and validation.

2.5.7.3 Representation of surroundings and urban context

Urban-scale Energy Digital Twins require not only buildings but also trees, ground surfaces, street furniture, and neighboring structures. These elements influence shading, microclimate conditions, and airflow patterns. LiDAR and photogrammetric datasets are usually capable of capturing such features, though semantic segmentation remains challenging. GIS layers define contextual information such as land use and vegetation types. Integrating these datasets with 3D models supports:

- district energy simulation
- solar potential mapping
- heat island analysis
- pedestrian comfort studies

2.5.8 Challenges in Extracting Geometric Features from geospatial datasets

Extracting geometric features from geospatial datasets presents several challenges due to data heterogeneity, scale, and acquisition methods. Datasets derived from sources such as LiDAR, photogrammetry, or satellite imagery often contain noise, missing data, and varying spatial resolutions, which affect the accuracy of feature identification. It is very difficult to detect geometrical elements such as edges, surfaces and structural boundaries because of the irregular sampling and occlusions. In complex environments and in particular in urban areas, the presence of a variety of objects such as buildings, vegetation and terrain, introduces additional ambiguity in feature extraction processes. In addition, the computational intensity of processing and analysing vast volumes of geospatial data leads to reduced efficiency. Incompatibilities in coordinate systems, data formats, and acquisition conditions also generate inconsistencies that hinder integration and interpretation. In addition, the absence of standard

validation frameworks and reference datasets presents a challenge in evaluating the quality of the extracted features. The challenges presented need to be addressed to improve the reliability of geospatial analyses and to support applications like mapping, modelling and environmental monitoring.

2.5.8.1 Data noise and occlusions

Occlusions from vegetation, vehicles, and architectural features often reduce dataset completeness. Noise from photogrammetry or low-density LiDAR can degrade accuracy. UAV-based workflows partially overcome occlusions by combining nadir and oblique imagery, but street-level occlusions remain problematic.

2.5.8.2 Variability in architectural styles

Buildings differ widely in geometry, materials, and façade patterns. Rule-based reconstruction approaches often fail to generalize across such diversity. Deep learning has improved robustness but requires large, labeled datasets, which are difficult to obtain for complex architectural features.

2.5.8.3 Interoperability issues

Integrating BIM, GIS, LiDAR, and thermal datasets remains a major challenge because of differing data schemas, coordinate systems, and attribute definitions. The thermal-enabled BIM-GIS workflow highlights progress in resolving interoperability barriers but also underscores the need for standardized methods frontiersin.org.

2.5.8.4 Indoor–outdoor connectivity

Indoor modelling is often disconnected from outdoor geometry, whereas energy simulations require continuous envelopes. Indoor point cloud classification is a research challenge due to clutter and limited visibility. The state-of-the-art in geospatial datasets and geometric feature extraction provides a strong foundation to develop reliable and detailed Energy Digital Twins. Advances in LiDAR, photogrammetry, thermal scanning, GIS-BIM integration and deep learning have significantly enhanced the accuracy and richness of 3D building and urban models. This research demonstrates clear progress in the integration of thermal measurements, the enhancement of façade reconstruction, the improvement of platform interoperability, and capturing of indoor and outdoor environments for

simulation-ready models. But there are still major challenges with data fusion, semantic interpretation, handling complex architectures, and maintaining consistent geometric detail over large urban areas. New techniques such as deep learning-based segmentation, multi-modal data integration and structured digital twin hierarchies are expected to bring improvements. As cities evolve towards dynamic and real-time digital twin ecosystems, the integration of geometric and thermal data and semantic structures will be necessary for precise energy modelling, operational monitoring and long-term sustainability planning.

2.6 Energy Modelling with windows for EDTs input

Windows are one of the most important factors in thermal performance of buildings, affecting heating, cooling and lighting needs in different seasons and times of the year. The optical and thermal properties such as solar heat gain coefficient (SHGC), U-value and visible transmittance of their impact on the energy consumption of a building is significant. Therefore, accurate energy modelling of windows is crucial for energy-efficient building design and retrofitting. This literature review reviews the current methodologies and tools used in window-specific energy modelling, with a focus on EnergyPlus, Ladybird Tools, ArcGIS, and the increasing relevance of point cloud data to augment building geometry and thermal simulations.

2.6.1 Energy Modelling with windows: different solutions

There is a range of software tools which can be employed for energy modelling with windows features for the urban environments. EnergyPlus is one of the prominently used, validated, dynamic simulation engine developed by the U.S. Department of Energy, widely utilized in energy performance modelling. It enables detailed analysis of fenestration systems through input parameters such as window type, glazing layers, shading devices, and material properties. Studies have shown that using EnergyPlus for window modelling allows simulation of complex interactions between solar radiation and building envelopes. This includes the *WindowMaterial:Glazing* and *WindowProperty:FrameAndDivider* objects to allow modelling of multi-layer glazing systems and framing effects, respectively, so that the heat gain/loss through windows can be completely evaluated. EnergyPlus can also read weather files (EPW format) and dynamic schedules allowing simulation over different climatic conditions and usage patterns. The software has been used in studies on optimising window-to-wall ratio (WWR), incorporating electrochromic glazing, and evaluating passive design

strategies. However, the accuracy of the geometrical input is a key factor for its effectiveness, which is often a limitation of the method when complex or existing structures are concerned.

Another option is Ladybird Tools, an open-source suite of tools that runs inside Rhino and Grasshopper and provides a visual programming interface to connect geometry to environmental simulation engines such as EnergyPlus and Radiance. It brings user interaction to parametric workflows, allowing for design optimisation and sensitivity analysis. Ladybird is particularly useful for windows giving detailed analysis of solar radiation, daylight simulation and view analysis. This helps in early design stages, and iterative refinement. Using Honeybee (part of Ladybird Tools), users can generate window properties and attach them directly to EnergyPlus simulations. Parametric modelling of WWR, shading geometry and glazing type allows designers to quickly explore multiple configurations. One of the major benefits is the ability to combine studies of radiation with energy models, providing in depth understanding of the trade-offs between natural lighting and heat gains through windows. GIS software tools especially ArcGIS, are increasingly used to integrate spatial and environmental data into building energy modelling. GIS can be used to map solar exposure, shadow analysis, and urban microclimate effects that are needed for accurate simulation of window performance in dense urban environments. ArcGIS can extract contextual parameters like adjacent building heights, street orientations and tree canopies factors that influence window exposure to solar radiation. ArcGIS has been used in combination with EnergyPlus in several studies to extract geospatial parameters that are used as inputs for building simulation models. For example, urban-scale energy modelling frameworks such as CityBES have been developed to simulate energy use intensity (EUI) at the building level with spatially resolved data. When focused on windows, GIS data helps make the assumptions about shading, reflectance, and ventilation potentials more accurate.

2.6.2 Point clouds for windows energy modelling

The inclusion of point clouds into energy modelling is an evolving trend overcoming the limitations of traditional CAD and BIM inputs. High resolution 3D building models with detailed window geometries, shading devices and irregularities of the facades can be derived from point clouds obtained by LiDAR or photogrammetry. This data can be critical for energy audits and retrofits where architectural drawings may not be available or are outdated. Point clouds can be processed to extract planar surfaces, fenestration dimensions and frame details

that are translated to simulation-ready geometry. Software such as Autodesk ReCap, CloudCompare, and Trimble RealWorks make this processing easier. Point cloud-based models integrated with EnergyPlus or Rhino (and eventually Ladybird Tools) offer a better representation of real-world conditions. The use of models based on point clouds has been proven to provide more accurate predictions of solar heat gain and internal thermal comfort (Volk et al., 2014). The integration of simulation engines, parametric modelling platforms, geospatial tools and high-resolution 3D data, offers a powerful framework for advanced window energy modelling. But interoperability and data fidelity remain big challenges. Current literature highlights much potential in the combination of point clouds with EnergyPlus and GIS for the generation of high-fidelity window models, but the field lacks standardised methodologies for such integration. Moreover, even if parametric tools allow rapid prototyping, the accuracy of results depends strongly on input data, underline the importance of a reliable geometric acquisition as the one provided by point clouds. Windows are complex components of the building envelope and must be modelled with great care to allow for accurate energy simulation. Strong analytical capabilities are offered by tools like EnergyPlus and Ladybird Tools, and ArcGIS adds a spatial layer of realism to the modelling process. The modelling process is enriched with the advent of point cloud technologies, offering high resolution as-built geometries. Future work should consider the optimisation of workflows for the integration of these tools and the establishment of standardised procedures for the inclusion of 3D scanning data in energy simulation models, especially for existing buildings and for urban retrofitting applications.

2.7 Energy Modelling with rooftops from point clouds as input for EDTs

The extraction of rooftop features plays a pivotal role in diverse applications such as urban planning, solar potential analysis, energy modeling, and cadastral mapping. With the increasing availability of high-resolution spatial data, especially from airborne laser scanning (ALS) and terrestrial laser scanning (TLS), point clouds have emerged as a primary data source for accurate three-dimensional (3D) representation of urban environments. This section presents a description of the evolution of the rooftop feature extraction techniques and the importance of the point clouds. Point clouds are explicit representations of the Earth's surface and objects on it, which are made up of a large number of spatially referenced points with elevation and intensity information. Compared to 2D

imagery, point clouds offer several benefits for rooftop extraction, such as a precise representation of surface geometry, detection of height discontinuities, and discrimination between vertical and horizontal features based on spatial relationships. Furthermore, point cloud is invariant to the variations of lighting and texture which usually impair the robustness of the 2D image-based methods. The average point density of airborne LiDAR data ranges from 1 to 20 points per square metre, enabling detailed analysis of rooftop structures such as ridges, dormers, parapets and chimneys. However, the raw data needs to undergo pre-processing steps like noise filtering, ground point removal and data thinning to ensure geometric consistency.

These preparatory processes are crucial for the effective application of subsequent computer vision techniques. Computer vision techniques provide a robust framework for rooftop feature extraction from point cloud data. By leveraging geometric properties, spatial continuity, and surface morphology, methods such as RANSAC, region growing, and edge detection have demonstrated significant efficacy in extracting and classifying rooftop structures. The integration of ancillary datasets such as building footprints enhances accuracy and contextual interpretation. While challenges remain in processing efficiency and data completeness, continued methodological refinement in 3D vision offers promising prospects for the precise and scalable analysis of urban rooftops.

2.7.1 Computer vision methods for rooftop extraction

Several computer vision techniques have been adapted or extended to work with 3D point cloud data for the purpose of rooftop feature extraction. One basic approach is the segmentation of the point cloud into planar surfaces. Algorithms such as RANSAC (Random Sample Consensus) for fitting planes are widely used because they are robust to outliers. RANSAC estimates the plane parameters by randomly selecting subsets of points and then identifies the inliers based on a distance threshold. This approach is particularly well suited to detecting the flat facets that are typically present on rooftops. Another typical approach is to implement region growing algorithms which group neighbouring points with similar normal vectors and curvature values into continuous regions. This approach exploits the local geometry of rooftops and can capture fine variations like changes in slope or curvature. Region growing with connectivity constraints allows to delineate rooftop boundaries and transitions between adjacent facets. In complex urban environments with overlapping roofs the edge detection of the space in 3D is needed. For 3D point clouds, edge detection can be adapted from

the 2D case by means of surface normal estimation and point density gradients. The presence of sharp edges helps to define roof planes, ridge lines and roof-wall junctions. These features are important for the reconstruction of correct building footprints and roof geometries. After segmentation, roof elements are often labelled and classified by a geometric rule-based classification. For example, planar regions with low inclination are identified as terraces, while sloped facets with specific orientations can be classified as gable or hip roofs. The elevation hierarchy of the segmented planes also aids in detecting superimposed features such as skylights or photovoltaic panels.

2.7.2 Integration of rooftop features with other GIS

The integration of 2D building footprint data further enhances the performance of rooftop feature extraction. When matched with point cloud datasets, building outlines serve as constraints for segmentation helping to remove unwanted elements like vegetation or infrastructure. The fusion of 2D and 3D data by projection and back-projection techniques allows an improved contextual understanding especially in dense built-up environments. They voxelize the point clouds, i.e. they divide the space into discrete 3D units. This gives them a nice well-structured format, which can be used with computational geometry operations. This approach reduces the complexity of the spatial analysis and speeds up the task of morphological filtering. However, voxel based approaches may result in loss of details especially for finely articulated roof structures. These classical computer vision techniques have been effective, but some limitations exist. The granularity of the extracted features is strongly affected by the density and quality of the point cloud. Occlusions are especially present in narrow urban canyons and cause data voids which affect completeness. Moreover, point clouds lack semantic information, which limits the differentiation of visually similar but functionally different rooftop elements. The high computational cost and the need for extensive parameter tuning also hinder large-scale implementation.

2.7.3 Energy Modelling with rooftops

The exploitation of rooftop surfaces for energy generation and conservation has gained considerable attention in recent years. Rooftop energy modelling entails the evaluation of solar irradiance potential, thermal properties, and structural suitability to optimize the placement and performance of photovoltaic (PV) systems and building-integrated solar technologies. Geographic information

systems (GIS), particularly ArcGIS Pro and QGIS, have emerged as central platforms for spatial data integration, analysis, and visualization in this domain.

At the same time, advances in computer vision algorithms and availability of 3D point cloud data open new avenues for accurate roof delineation, occlusion detection and surface orientation estimation. This review summarises the existing literature on the use of ArcGIS Pro and QGIS in rooftop energy modelling, discusses the application of computer vision techniques for the extraction of rooftop features and explores the use of point cloud data to improve model accuracy. Applying structured computer vision techniques to point cloud data sets appears to be a promising way forward for detailed rooftop reconstruction, an important requisite for accurate urban energy modelling. These datasets can be very useful for the assessment of the potential for solar energy, the thermal behaviour and the energy performance at building and neighbourhood level. The increasing trend for urban planners and energy modellers to adopt more granular data-driven approaches will only further increase the role of rooftop information extracted from point clouds in the development of sustainable and energy efficient urban environments. GIS platforms are important tools in energy related studies for management, processing and visualisation of spatial data. ArcGIS Pro is often used to estimate rooftop solar potential because of its powerful spatial analysis functions, and integrated meteorological and remote sensing data (Delphine Khanna, 2023; Parida et al., 2011). Topography-corrected maps of solar radiation, slope and aspect are derived from digital elevation models (DEMs) and the Solar Analyst extension. (Anselmo & Ferrara, 2023) introduced a workflow within ArcGIS Pro for the creation of high-resolution irradiance raster layers from LiDAR derived DEMs for the improvement of site suitability analyses for PV installations. Additionally, the urban canopy models in ArcGIS Pro can be used to model shading of neighbouring buildings on buildings and vegetation for a more complete assessment of “effective” solar access. Other studies have used the ModelBuilder environment in ArcGIS Pro to automate processing of multispectral imagery and perform spatial analyses in batch over larger urban areas. This minimises the manual work and the risk of human errors to a large extent. Analysis of rooftop heat flux and radiation using thermal imagery and cadastral and building footprint data in ArcGIS Pro. Estimation of heat losses and feasibility of combined solar photo voltaic and thermal (PVT) systems using co-registration of thermal infrared (TIR) images and vector rooftop layers. The application of this multi-layered approach allows the complete assessment of the energy flows which is necessary for the development of energy efficient retrofitting actions.

QGIS has emerged as a robust open-source alternative to proprietary GIS platforms, offering similar functionality through its plugin architecture. The QGIS “Solar Radiation” plugin does raster-based modelling of irradiance, in a similar way to ArcGIS Solar Analyst, and uses DEM layers as inputs to calculate daily and annual solar insolation. The QGIS Solar Radiation plugin has been validated by ground-truth measurements (Romero Rodríguez et al., 2017), with mean absolute errors below 5%, demonstrating the viability of the proposed method for urban solar assessments. Moreover, QGIS supports integration with external processing tools like GRASS GIS and SAGA GIS for advanced terrain analysis and automated batch processing. QGIS also allows import of building footprint data in different formats (e.g. GeoJSON, Shapefile) for fast rooftop delineation and classification. When combined with satellite imagery or aerial orthophotos, users can manually or semi-automatically digitise rooftop polygons for energy modelling input. The ability to script in Python using the PyQGIS API further enhances reproducibility; researchers have developed scripts to extract rooftop centroids, compute area and aspect, and produce input tables for photovoltaic yield simulation tools such as PVGIS or SAM (System Advisor Model). The extensibility of QGIS and its free license makes it particularly attractive for large scale studies in resource constrained settings.

Computer vision methodologies are central to the conversion of raw point clouds into usable rooftop models. To separate rooftop elements from urban scenes, pre-processing steps such as denoising, ground filtering and occlusion handling are required. Usually, plane fitting algorithms such as RANSAC (Random Sample Consensus) and region-growing methods are employed to segment the planar surfaces that represent the roof facets. These can then be grouped into archetypes (eg gable, hip, flat roofs) to enable standardised energy modelling inputs. Furthermore, rasterised height maps (Digital Surface Models) derived from point clouds can be enhanced using sophisticated morphological operations and edge-detection filters to more accurately delineate roof ridges and valleys. These structural features are important for the calculation of roof surface orientation and tilt angles, which have direct influences on the simulations of solar radiation absorption and heat transfer. These reconstructions have a strong impact on rooftop photovoltaic (PV) potential and cooling/heating load simulation. One of the most well-known uses for rooftop models generated from point clouds is the estimation of solar energy availability. Once the roofs are reconstructed, algorithms like shadow casting, sky-view factor (SVF) calculation and time-series solar irradiation models are implemented. These in conjunction with meteorological data allow for accurate estimation of insolation profiles. The study

by show that models with 3D rooftop morphology result in substantially more accurate estimation of PV potential than footprint-based approaches with 2D morphology.

In addition, spatial sampling of rooftop grids is often employed to simulate temporal variation of sun angle and seasonal effects. The derived geometry can be processed by tools such as Solar Analyst or the *r.sun* module in GRASS GIS in order to compute annual or hourly solar gain, which can be integrated into building energy simulators such as EnergyPlus or TRNSYS. In addition to solar potential, the geometry of the rooftop is a key factor in thermal behaviour due to its interaction with external temperature, albedo and convection processes. The volumetric and surface parameters derived from point clouds allow to compute heat flux, surface to volume ratios and roof insulation estimates. These parameters are crucial for building models of the thermal envelope. Incorporating such spatial parameters in energy modelling tools allows to assess energy demand, in particular cooling demand in summer and heating demand in winter. For simulation tools, roof geometry inputs define the surface exposure and boundary conditions for heat transfer simulations.

2.8 Development of Energy Digital Twins

Energy Digital Twins (EDT) represent an evolving frontier in the analysis of building performance. These are dynamic, data-rich virtual models of physical buildings that can be used for simulation, monitoring and control. Accurate EDTs are essential for evaluating heat exchange, solar gain and energy demand, and their development relies centrally on the geometric and semantic representation of building envelope elements (e.g. rooftops and windows). High-resolution spatial datasets in the form of three-dimensional point clouds obtained through LiDAR or photogrammetry have allowed unprecedented detail in as-built modelling. This review discusses the contribution of point cloud data and computer-vision based reconstruction techniques for the acquisition of window and rooftop geometries, which are essential for the development of energy-relevant digital Twins. Rooftops and windows are the main building surfaces interacting thermally and radiatively with the environment. The accurate modelling of rooftop geometry is important for the determination of solar exposure, shading patterns, insulation quality and potential for photovoltaic (PV) integration. Similarly, windows are the main channels for solar gain, daylighting, and conductive heat loss, especially in

climates where heating dominates. Building features such as orientation, size, glazing properties and shading devices directly affect the building energy performance metrics such as annual heating and cooling loads.

The geometric fidelity of these envelope components is therefore of interest for digital twins that seek to simulate transient energy behaviour under realistic boundary conditions. Any simplification or omission may lead to under or over estimation of solar gains, thermal losses or HVAC loads. In this context, the traditional methods based on building footprint data or schematic representations are not enough and so there is a need for 3D spatial data sources. After rooftops and windows are extracted, their geometry and orientation are used to parameterise engines for thermal and daylight simulation. EnergyPlus, IDA ICE and TRNSYS can accept these inputs through 3D intermediate modelling environments such as Rhino/Grasshopper or through BIM compatible formats such as IFC and gbXML. These systems model solar heat gains, daylight availability and ventilation loads, and contribute to the performance backbone of the digital twin. Moreover, spatial properties derived from point clouds can be associated with material and boundary condition metadata. For example, windows can be assigned parameters such as transmittance and U-value based on their detected type and size. Depending on the energy modelling scenario, rooftops are associated with either the depth of insulation, reflectivity or integrated PV efficiency.

(Biljecki & Ohori, 2015; A. N. Wu & Biljecki, 2021) in their study show how the LiDAR point clouds enable accurate reconstruction of complex rooftop geometries. This, in return, enables energy modelling as it provides accurate solar radiation estimation. Roof slope and orientation, as well as shadow casting, are crucial features to simulate solar energy potential and have been widely assessed from LiDAR-derived DSMs. These methods allow for the inclusion of rooftop geometries in building energy simulations, improving the accuracy of solar irradiance and energy efficiency estimations (Zhou & Hu, 2025). The combination of point cloud data and computer vision has dramatically improved the accuracy of energy models. (Soergel et al., 2021) employed multi-view imagery and structure-from-motion to reconstruct roof geometries, illustrating that image-based techniques can complement LiDAR data to improve rooftop modelling. High-resolution rooftop models improve accuracy of solar potential assessment for building-integrated photovoltaics (BIPV) (Castellanos et al., 2025; Hu et al., 2023). These detailed point cloud data-based models can be integrated in simulation software to simulate annual solar exposure of rooftops including

shadowing, solar reflectivity and material properties. Likewise, point-cloud based window models permit more precise simulations of energy loss through windows by factoring in the type of glazing, the size of the frame and the orientation.

2.19 Challenges identified in the existing studies

The creation of accurate and functional Energy Digital Twins (EDTs) requires more than just detailed 3D geometry; it also depends on the integration of reliable building metadata (M. E. Ali et al., 2024; Attaran & Celik, 2023). These include complex roof geometries such as dormers and chimneys which are often difficult to model accurately using point cloud data. Furthermore, the accuracy of the rooftop segmentation is further reduced by the incomplete point clouds and occlusions from neighbouring buildings or vegetation. This makes it difficult to obtain accurate roof slope and orientation, which are vital to solar energy modelling. Detecting windows in façades is challenging due to the low reflectivity of glass, frequent occlusions by balconies or vegetation, and small size or misalignment of windows in LiDAR data. These problems lead to missing or misclassified openings which has a direct impact on the calculations of heat loss and solar gain.

In addition to geometry, EDTs require important non-geometric inputs, which are often missing or inconsistent in existing studies. These include the energy rating of buildings, the year of construction, renovation history, material properties, building occupancy or population data, and typical usage patterns (Zirak et al., 2020). Without such parameters energy simulations lack the context of realistic results. For instance, a given roof geometry could behave differently based on the quality of the insulation or on how many occupants are using heating or cooling systems. Extracted geometries usually do not have semantic data and this results in underestimated energy consumption or performance in simulations. At the urban scale, windows and fine façade details are often omitted and building-level metadata is generalised, reducing the effectiveness of the digital twin for energy policy, retrofit planning, or operational decision-making. This PhD research addresses these limitations by combining the improved geometry extraction procedures from the point clouds with structured metadata gathering and integration for the development of an EDT ecosystem. By focusing on rooftops, windows, and critical building attributes, this research aims to contribute toward a more reliable, operational and application-ready Energy Digital Twins.

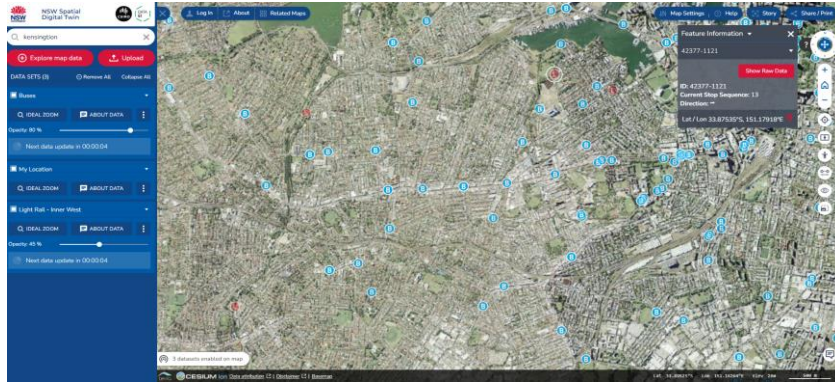
Chapter 3

Implemented Use Cases of Digital Twins

Several types of Digital Twin implementations have been established globally for various applications and use cases. These systems are employed for urban planning, environmental assessment, infrastructure management, and energy research. Cities and organisations create DTs tailored to their requirements and accessible data. The extent of these implementations varies from complete cities to singular items. They integrate many datasets to facilitate analysis and decision-making. The diversity in these implementations illustrates how DTs can adjust to various applications and use cases. This section provides curated real-world implementations across the globe to demonstrate their practical applications.

3.1 State of the art Implemented DT use cases across the world

Figure 5 (a) and Figure 8 (b) illustrate the UDT of an urban built environment for the cities of Sydney and Liverpool in Australia with 3D datasets . The NSW and Liverpool digital twins have been used to support urban planning, infrastructure management, transportation, traffic monitoring, and emergency response through real-time geospatial data and analytics. These UDT implementations also enable livability assessments and community engagement by visualizing environmental and traffic conditions for sustainable city planning.



(a)



(b)

Figure 5: Illustration of (a) Urban Digital Twins for Transport Monitoring from Sydney, Australia, taken from (DCS Spatial Services & NSW Spatial Services, 2024) , (b) 3D Urban Digital Twin from Liverpool, Australia, taken from (Diakite et al., 2022; FrontierSI et al., 2022)

The Rotterdam Digital Twin project, as presented below in Figure 6, is a flagship initiative within the city's broader 'Digital City' strategy, which aims to transform Rotterdam into a data-driven organization. The main aim is to assist urban planning by providing a comprehensive, dynamic digital model of the city. The digital twin is intended to supplement and enhance existing participation processes, not to replace them, stimulating more active citizen participation, supporting climate adaptation goals and preparing for regulatory frameworks like the Omgevingswet. It mixes physical infrastructure with real-time digital data and socio-economic processes. It's one easy-to-access platform, built for many stakeholders. Advanced 3D city models, the integration of semantic data by ontologies and new tools, such as Augmented Reality (AR), are included in the

model to increase engagement and data clarity. The city also plans to develop a shared data space, possibly a data marketplace, in line with the European Data Strategy and OGC web standards such as 3DTiles for point clouds and DTM serving. Although Rotterdam is considered a leader in this area, it still faces challenges, particularly in terms of data interoperability, real-time IoT sensor performance, and organizational capacity. The full vision of a platform-based citywide digital twin is still taking shape, but its ambitions signal a shift towards more transparent, participatory, and responsive city governance.

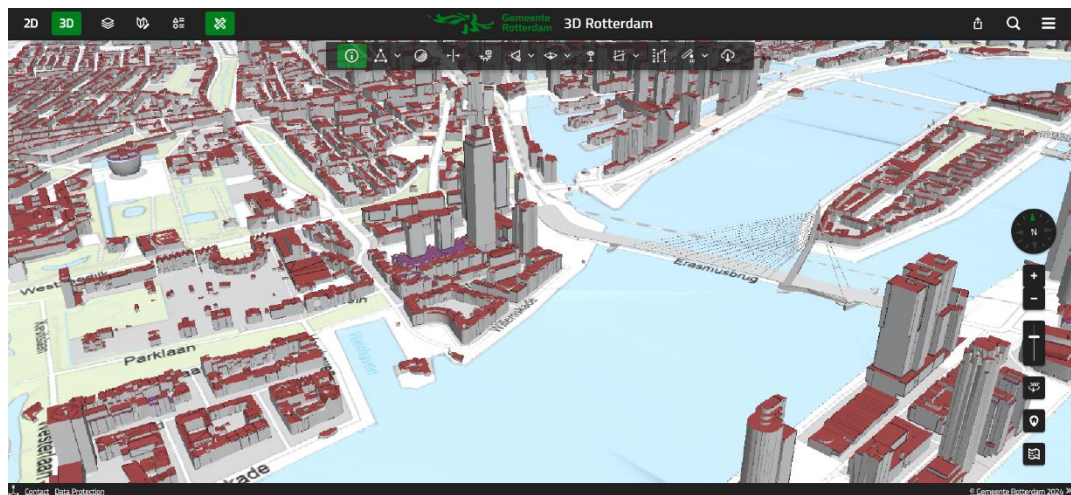


Figure 6: Home page of the 3D viewer implemented in the UDT public platform of the city of Rotterdam, taken from (Gemeente Rotterdam, 2024).

Figure 7 below presents the implementation of the Munich digital twin from Germany. Munich DT discussed how Munich is using its Digital Twin technology to address the challenges of climate change, particularly in its historic city centre. By integrating the PALM-4U urban climate model into the Digital Twin, city planners can simulate and visualize heat distribution, identify urban heat islands, and assess the effectiveness of various cooling measures.



Figure 7: 3D planning visualization with the Digital Twin Munich, taken from (Amini et al., 2023)

The Digital Twin Munich (DZ-M) project aims to create a dynamic, semantically rich digital model of the city, focusing on street networks and urban mobility . It integrates data from heterogeneous sources and uses SUMO for traffic simulations, requiring compatible data structures and conversion techniques . The model supports OpenStreetMap, CityGML, and GTFS standards, serving as a valid working example of how to integrate authoritative and volunteered geographic information into a single framework that also supports public administration. Physical simulators and a 3D Virtual Reality (VR) environment in Unity validate spatial accuracy and user behaviour. Iterative development and simulator studies ensure data quality, aiming to improve urban mobility management through realistic, high-fidelity digital twin representations. However, the current implementation lacks public access and open updated documentation. Figure 8 below presents the Cesium-based visualization of 3D city model of the city of Helsinki for the development of an operational digital twin for the city.

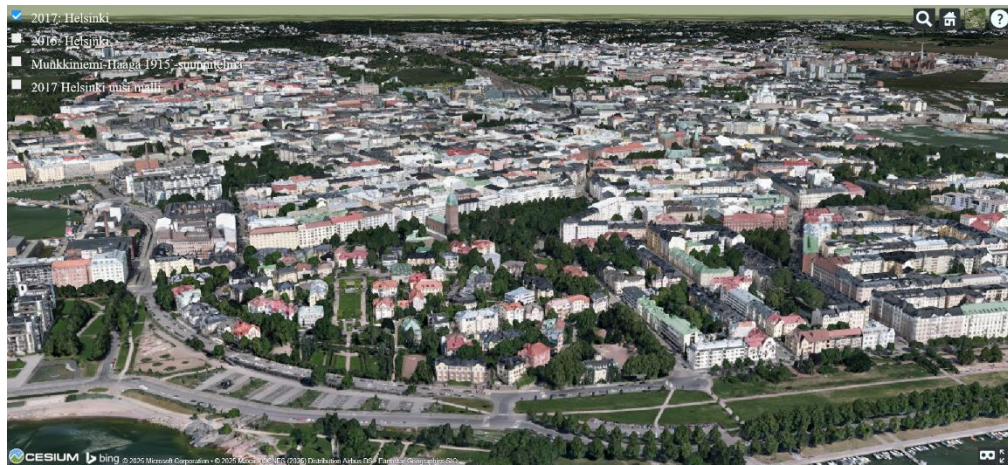


Figure 8: View of the 3D city model Cesium-based viewer developed for the digital twin for the city of Helsinki, taken from (City of Helsinki, 2025)

Singapore’s digital twin is a comprehensive virtual representation of its physical urban environment, designed to mirror real-world entities and urban dynamics . Central to this initiative is the integration of diverse data sources such as geospatial, semantic, sensor-based, and real-time inputs from IoT, GIS, photogrammetry, and BIM to support decision-making in areas like planning, sustainability, and infrastructure management. The main applications are in port operations, where digital twins improve situational awareness and optimal terminal efficiency, and in urban planning(Ramani et al., 2023), where they support scenario modelling and public engagement. More importantly, Singapore’s approach is to prioritise sustainability and public perception in landscape and planning processes, encouraging inclusive urban development. From a technological perspective, Singapore’s sophisticated digital infrastructure facilitates the deployment of these complex systems. The initiative “Virtual Singapore” exemplifies this effort, evolving from static 3D models into dynamic platforms enriched with real-time data and analytical tools for advanced insights extraction. These digital twins aim to inform smarter, more sustainable urban development strategies and create more responsive and liveable cities.

Another operational and working example of UDT implementation with a special focus on disaster mitigation and sustainable urban planning is the PLATEAU project, as presented below in Figure 9. Launched in 2020, this nationwide initiative, coordinated by the Ministry of Land, Infrastructure, Transport, and Tourism, was designed as a digital solution to the need for periodic updating of urban planning data and documentation, which since the late 1960s

has been governed by the constant production of paper-based reports that often resulted in data loss and incompleteness. Built on top of Free and Open-Source Software for Geospatial (FOSS4G), the project relies on the open data culture as well as extensive open documentation through the implementation of use-case focused guides on the initiative's GitHub spaces released with permissive licenses (Apache 2.0), allowing re adaptability for their projects. Current use cases driven by community needs range from urban modelling and planning to disaster simulation, with a particular focus on community engagement workshops that leverage the potential of both virtual and augmented reality solutions. The FOSS4G-based adopted software architecture for the interactive platform “View App” extensively uses Cesium technologies for its front-end development, ensuring seamless visualization of 3D models in CityGML format deployed on the web in 3D tiles format compliant with the latest OGC standards for lightweight rendering and exploration. Figure 9 below presents a snapshot of UDT project led by Ministry of Land, Infrastructure, Transport and Tourism for Japan.

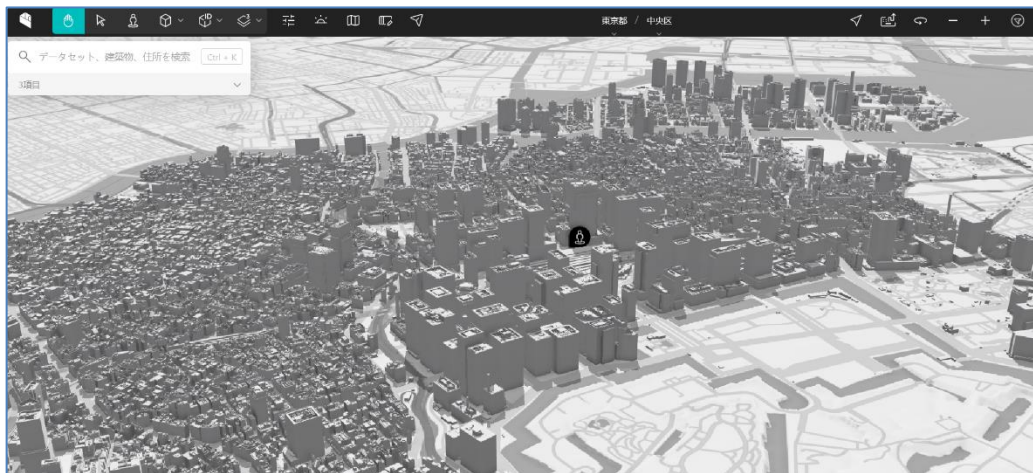


Figure 9: PLATEAU View App for the UDT project led by Ministry of Land, Infrastructure, Transport and Tourism for Japan, taken from (MLIT Japan, 2025).

These operational illustrations and examples above highlight diverse applications and underscore reproducibility challenges related to technological variations, financial constraints, and standardization differences. Emerging solutions and future directions advancements in GIS tools, 3D modelling, artificial intelligence, machine learning, and big data analytics represent promising developments enhancing digital twin reproducibility. The availability of large

amounts of data and AI-based analytics enables more precision, faster processing and scalable implementations and is critical for real-life digital twin applications. Standardisation of data formats, increased transparency of methodology and open-source solutions are necessary to address the reproducibility. Future research should target the integration of scalable, transparent, and robust technologies, which would significantly increase the reliability and applicability of digital twins in a variety of geospatial settings.

As shown in Table 3 below, the scope of Digital Twin implementations is highly varied, but their scope and purpose are always the main drivers. City-scale digital twins such as Virtual Singapore, Helsinki 3D+ and New York City are primarily based on geospatial data such as LiDAR, photogrammetry and CityGML for urban planning, environmental analysis, and risk assessment. In contrast, infrastructure and asset-centric twins depend more on operational datasets such as SCADA, IoT and engineering models, indicating a shift from geographical representation to system performance evaluation. The type and complexity of data used will be directly related to the level of implementation, from the facility to the national level. Energy-centric twins focus on real-time and network-oriented data to enable the monitoring, forecasting and optimisation of supply-demand interactions. Table 3 indicates that Digital Twins are context-specific systems where the selection of data, the spatial scale, and the application intent are closely interrelated.

Table 3: Summary of implementations of digital twins, their applications, geospatial datasets used and scale of implementation.

DT implementation	Application	Geospatial Dataset	Scale
Virtual Singapore (Y. Du et al., 2024)	Urban planning, environmental simulations.	LiDAR, BIM, CityGML.	City-State
Helsinki 3D+ (Hämäläinen, 2021)	Solar potential, energy analytics.	Photogrammetry, Laser.	City-wide
Virtual Zurich (Schrotter & Hürzeler, 2020)	Infrastructure, heat mapping.	3D Buildings, ArcGIS.	City-wide
Barcelona DT (Diaz-Sarachaga, 2024)	Social impact, traffic modeling.	IoT, Supercomputing data.	City-wide
London DT (VU.CITY, 2026)	Underground assets, housing.	OS MasterMap, BIM.	City-wide
Rotterdam DT (Arthur De	Asset maintenance,	Point clouds, IoT.	Port/City

Jaeger, 2024; Gemeente Rotterdam, 2024)	water safety.		
NSW Spatial DT(DCS Spatial Services & NSW Spatial Services, 2024; FrontierSI et al., 2022)	Bushfire and flood emergency.	LiDAR, Satellite, GIS.	State
S-Map (Seoul) (Seoul Metropolitan Government, 2026)	Traffic and pollution response.	IoT, 3D GIS.	City-wide
Shanghai DT(C. Liu & Tian, 2023)	Emergency management, signal timing.	CCTV, Satellite, IoT.	City-wide
New York City DT(Mydlarz et al., 2019)	Flood risk and zoning.	LiDAR, 3D Photogrammetry.	City-wide
Stockholm 3D (Drive Sweden, 2022)	Daylight and noise analysis.	3D Mesh, CityGML.	City-wide
Gothenburg DT (Maiullari et al., 2023)	Urban densification testing, energy efficiency.	CityGML, Laser scanning.	City-wide

3.2 Energy Digital Twins : Implementation and use cases

The essence of an Energy Digital Twin is the integration of geospatial and non-geospatial datasets. These encompass architectural geometry, diverse material characteristics, meteorological data, energy usage statistics, and operational metrics. One of the main issues in implementation of EDT is the requirement of semantic and geospatially consistency across various datasets. The geospatial inputs are typically characterised by different levels of detail and accuracy in the form of 3D city models or point clouds. In order to transform them to simulation-ready models, a lot of pre-processing is required, such as geometry simplification, topology repair and attribute enrichment. A key implementation decision is the granularity of models. Finer-grained models may achieve higher accuracy, but they also come with a significant increase in both computation and data need resulting in a trade-off between the model accuracy and scalability.

Integration of physical simulation engines with real-world data streams is a key part of implementation. Energy Digital Twins often use simulation tools such as building energy models to mimic thermal behaviour, energy flows and system performance. Still, these models need to be constantly calibrated with real-time or historical data to stay relevant. Calibration is a difficult task, since the differences

between the simulated and the observed data can arise from measurement errors, too little input data or model simplifications. This creates a feedback loop that requires iterative refinement of the twin, hence raising questions on convergence, stability and reliability. Moreover, the temporal resolution of data, from hourly meteorological inputs to sub-minute sensor readings, adds to the complexity of synchronisation and processing.

Table 4 below illustrates that Energy Digital Twin applications are primarily influenced by the interplay among use case, data requirements, and Level of Detail (LoD). Extensive applications like urban energy mapping and grid simulations depend on lower Levels of Detail (LoD 0 – LoD 2), where simplified geometry is adequate for system-level analysis. Conversely, building retrofitting and indoor optimisation necessitate elevated Levels of Detail (LoD 3 – LoD 4) to accurately represent façade intricacies and internal systems. The trend distinctly illustrates a trade-off between scalability and precision, wherein enhanced detail augments analytical correctness but necessitates more intricate datasets. It also underscores that various sensing sources, such as airborne LiDAR or mobile mapping, are chosen according to the necessary geometric precision.

Table 4: Various use cases which can be addressed by EDTs and their required datasets.

Use Case	Required Datasets	Required LoD
Urban energy mapping (Jeddoub & others, 2023; Naserentin & Logg, 2022)	Aerial photogrammetry / LiDAR, building footprints	LoD1–LoD2
Building retrofit analysis(Xue et al., 2020)	Mobile LiDAR/ SLAM, façade features	LoD3
Indoor energy optimization (J. Zhang & Cheng, 2021)	BIM + sensors	LoD4
Grid / microgrid simulation (Kumari & others, 2023)	Network + GIS datasets	LoD0–LoD1

Beyond deployment, the efficacy of Energy Digital Twins is strongly dependent on the clarity and relevance of their use cases. A well-defined use case guides model development, identifies data requirements, and specifies evaluation criteria. Without such a foundation, EDTs risk becoming generic platforms with no practical application. Importantly, use cases should be motivated not by

technological capabilities, but by real-world problems and stakeholder requirements.

One of the most exciting applications for EDTs is the optimisation of energy performance at building level. Here, the digital twin serves as a decision support tool for the facility manager to evaluate the effect of operational changes, retrofit measures and control techniques. For example, an EDT can be used to characterise the impact of different heating or ventilation schedules on energy use and indoor comfort. The reason is obvious: buildings consume a large share of the world's energy, and even small efficiency improvements can lead to big savings. But for this use case to be successful, we need high-quality input data and the ability to calibrate the model against real performance. One major application is predictive maintenance for energy systems. An EDT continuously observes system behaviour and compares this behaviour to expected performance, to help identify abnormalities that may be symptoms of faults or degradation. This is particularly true for complex systems such as district heating networks and renewable energy systems. The goal is to reduce downtime, extend the life of assets and minimise maintenance costs. But deploying this use case requires strong baseline models and effective techniques to separate normal variation from serious problems.

In a broader context, Energy Digital Twins can be useful in urban energy planning. Urban planners and municipalities use EDTs to compare different development scenarios, analyse policy impacts and create more sustainable energy systems. A city-scale twin can simulate the effects of integrating renewable energy sources, improving building insulation or changing the shape of the urban area. This is a strategic goal, to allow evidence-based decision making in the transition to low-carbon cities. However, this use case suffers from important problems in terms of data availability, model scalability and capturing complex interactions between buildings, infrastructure and environment. Energy Digital Twins have the potential to enhance demand response and grid interaction. EDTs represent the dynamic relation between energy supply and demand and can increase grid stability and improve load distribution. An EDT can be used to emulate the effect of temporal variations in energy consumption, such as intelligent appliance or storage scheduling, on peak demand. The aim is to increase the efficiency and robustness of energy systems, especially in the face of the growing variability of renewable energy sources. This use case has a strong connection to grid data and presents problems of coordination between many actors including utilities, building owners and tenants. The use case of the

integration of the EDTs with climate adaptation techniques is growing. Buildings and energy systems must adapt to new temperature patterns, extreme weather events and changed demand profiles as the climate changes. The Energy Digital Twin could also be used to assess existing systems' resilience and explore adaptation options (e.g. passive cooling, enhanced insulation). Long term sustainability is the motivation and risk reduction. But adding future climate scenarios into the twin adds layers of uncertainty and complexity.

The practical implementations summarised in the Table 5 below reveal a consistent and critical pattern in the development of Energy Digital Twins: the intended application drives the selection of geospatial datasets and the Level of Detail (LoD), not data availability. Across the case studies, lower levels of detail (LoD0-LoD1) are widely used for large scale applications such as urban energy mapping or grid-level optimisation, where computational economy and scalability outweigh geometric precision. For the application focus on individual buildings LoD2 is sufficient for the calculation of total energy demand whereas LoD3 and LoD4 are required for detailed studies on façade features, windows and internal systems like HVAC. This trend demonstrates a clear trade-off between accuracy and computational expense, with increased geometric detail improving simulation fidelity but considerably increasing data processing and modelling complexity.

Table 5: Practical implementations of EDTs around the world with various geospatial datasets.

Implementation / Case Study	Geospatial Datasets Used	Level of Detail (LoD)	Specific Energy Application
TUM2TWIN Urban Digital Twin (Wysocki et al., 2026)	Multimodal datasets: terrestrial, mobile, aerial LiDAR point clouds, images, 3D city models	LoD2–LoD3 (with façade-level detail reconstruction)	Urban-scale energy analysis (e.g., solar potential, energy demand modeling)
ArcGIS-based Building Digital Twin Workflow (Esri, 2020)	classified point clouds	LoD1–LoD2	Building energy baseline modeling and urban energy mapping
Indoor-Outdoor Building (BIO) Dataset (Cao & Scaioni, 2023)	Labeled point clouds + meshes (indoor & outdoor building environments)	LoD2–LoD3	Indoor-outdoor energy flow analysis (ventilation, thermal zones)
Virtual Shizuoka Digital Twin (JG Times, 2026)	Large-scale regional LiDAR point cloud datasets	LoD1–LoD2	Regional energy planning, disaster-energy resilience
Smart Campus Digital Twin (BIM + GIS Integration) (N. Sharma, 2025)	BIM (IFC), IoT sensor data, 3D geospatial models	LoD3–LoD4	Real-time energy optimization (HVAC, indoor climate control)
Industrial Facility Digital Twin (CLOI framework) (Agapaki & Brilakis, 2021)	High-density industrial LiDAR point clouds	LoD2–LoD3	Energy monitoring and optimization of industrial systems
3D Survey-based Building Energy Digital Twin (Roman et al., 2025)	3D surveying data (LiDAR, photogrammetry), building geometry datasets	LoD2–LoD3	Building performance simulation (heating/cooling loads)

A typically pattern of observation is the centrality of point cloud data as the geometric basis for many implementations. LiDAR and photogrammetric datasets contain a wealth of spatial information, yet they are unstructured and lack semantic meaning. Therefore, they cannot be directly used for energy simulations without extensive pre-processing steps such as segmentation, surface reconstruction and conversion into structured formats such as CityGML or BIM. This transformation pipeline is not only technically challenging, but also represents one of the major bottlenecks for scalable Energy Digital Twin development. Moreover, the wide range of applications from urban planning to building retrofitting and industrial monitoring suggests that there is no unique modelling approach. Instead, every implementation finds a particular detail/efficiency trade-off that is specific to its purpose, which further emphasises the importance of application-driven design strategies.

The conceptual framework complements these observations and shows the sequential dependence between geospatial data, processing steps, Level of Detail and final energy applications. It states that the raw geospatial data sets are detailed but not directly usable, and need to be transformed into structured representations, possibly with the identification of the required building features. In this pipeline, LoD is the main decision layer that determines the model complexity and suitability for particular use cases. The LoD choice can be inappropriate leading to models that are too simplistic to capture crucial energy behaviours or models that are too complex, computationally expensive and difficult to maintain. LoD therefore serves as a direct link between data preparation and simulation readiness and thence to meaningful application outcomes.

In combination, the table 5 and framework reflect a fundamental limitation of current Energy Digital Twin practices, namely, the lack of standardised methodologies for systematically selecting and deriving appropriate Levels of Detail (LoDs) from geospatial datasets, particularly point clouds. Existing implementations show the feasibility of integrating geometry with energy modelling but are usually based on ad hoc workflows and decisions for each case. This points out an important research gap, where future work has to focus on developing structured, scalable approaches, which align data processing, LoD generation and application requirements. It is important to bridge this gap to move Energy Digital Twins from isolated implementations towards more generalised, efficient and reliable systems. Not all potential applications require the effort to develop a fully functional Energy Digital Twin. More often simpler analytical models or statistics give enough insight at a lower cost. A key question in the

development of EDTs is whether the increased complexity and resources required are justified by the anticipated benefits. This demands a cost-benefit analysis which takes into account technical performance, usability, maintainability and stakeholders' viewpoints.

Another important aspect is the human side of EDTs. The focus is on data and models, but the ultimate goal is to enable decision making by people. This requires user friendly interfaces, clear visualisation of results, and transparency about the assumptions and constraints of the model. But a twin, no matter how technologically advanced, will have limited impact if people do not trust it, or understand it. Therefore, user-centred design must be an essential ingredient in the implementation of EDT. Energy Digital Twins have the potential to enhance the awareness and control of energy systems, but their success hinges on thoughtful implementation and clear use cases. The main challenges are data integration, model calibration, interoperability, scalability and uncertainty management. Equally important is the need to ground the development of EDTs in targeted, pragmatic applications to real world problems. Energy Digital Twins can deliver tangible benefits in energy efficiency, sustainability, and system resilience, through the deliberate alignment of technology capabilities with user needs and contextual constraints, and thus go beyond the level of conceptual potential.

Chapter 4

Conceptual framework and research methodology

This section of the dissertation presents the conceptual framework and methodological structure for developing an Energy Digital Twins (EDTs) from point cloud datasets, with particular focus on window and rooftop-based energy modelling. The framework is divided into four major sections: acquiring data and processing, feature extraction from point clouds, energy modelling using extracted features, and an integrated approach for developing an operational EDT system.

4.1 Inputs required for an operational EDT system

An operational Energy Digital Twin (EDT) system requires the integration of detailed and structured datasets that represent both the physical and operational characteristics of buildings. In the context of Turin, Italy, high-resolution 3D geometric data serves as the foundation, acquired primarily through LiDAR and photogrammetry. This includes precise building footprints, height profiles, and detailed rooftop geometries such as slope, orientation, and surface area critical for solar energy modeling. Accurate window detection is also important because it provides information about the size, orientation, and location of the window. Windows are a major component of thermal exchange and daylighting, and their presence directly impacts the accuracy of energy simulations. Such geometrical inputs are usually processed by feature extraction algorithms (e.g. Random Forest) on dense point cloud datasets. Besides geometry, semantic attributes of buildings are required for realistic energy modelling. These include the year of construction,

which is related to regulatory changes and standards of construction material; the building typology (e.g. residential, commercial); and the thermal properties of material such as U-values for walls, roofs and glazing. For example, the building stock of Torino is mainly composed of residential buildings built in the 1960s and 1970s, which are characterised by low insulation standards. Moreover, the inclusion of dynamic parameters such as the historical energy consumption, energy efficiency ratings (if available) and occupancy profiles further enhances the reliability of energy load predictions. The seasonal performance assessment requires the inclusion of climate datasets (temperature, solar irradiance, wind speed) for the local weather of Turin, characterised by cold winters and warm summers.

In addition to physical and environmental datasets, operational inputs like population density per building, daily usage schedules and appliance load profiles are required for dynamic simulations. The inputs are the internal heat gains and the patterns of HVAC operation. The urban-scale model in Turin is also affected by morphological constraints such as shading from surrounding buildings and vegetation. An EDT takes all these datasets, combines them into one digital representation, and can then accurately assess the solar potential, thermal losses through windows and roofs, and overall energy behaviour. Such a framework can support building-level retrofitting strategies and inform energy policy planning at the municipal scale.

An Energy Digital Twin (EDT) combines Building Information Modelling (BIM), Internet of Things (IoT) sensors, geospatial datasets and energy metrics into an evolving virtual twin to provide real-time monitoring of physical energy infrastructure. A centralised RDBMS handles complex datasets with a higher level of data integrity and provides a secure basis for advanced analytical queries and simulations. Dynamic update methods and geospatial data surveys maintain a high-fidelity relationship, ensuring that the digital model progresses in full synchronisation with the physical world. The EDT monitors energy flows and forecasts peak demand, thus optimising consumption, reducing carbon emissions and allowing the integration of renewable energy sources. Role-based, strategic access allows actors to communicate securely to make data-driven decisions that balance the stability of the grid with the long-term sustainability of the city.

The EDT system operates on the basis of integration of external data sources. Weather data is important as it gives inputs like temperature, solar radiation, wind speed and humidity. These parameters influence the thermal performance of

buildings and are used to simulate the hourly or sub-hourly energy performance. It also contains occupancy patterns, internal heat gains and operational schedules in addition to weather data for a more accurate representation of how buildings are actually used. Such inputs may be obtained from standard assumptions or, where available, from measurements.

After defining the input data, the simulation engine calculates energy related outputs such as heating and cooling loads, indoor temperature variations and energy demand profiles. These outputs are linked back to the spatial model, allowing the energy performance to be visualised and analysed at different levels of detail. For example, the rooftop surface solar energy potential can be assessed, and the effects of window configurations on heat losses and daylight availability can be analysed.

A core aspect of the EDT system is the support for updates and iterative improvements. As new data becomes available the digital twin can be improved in accuracy and relevance. Updates can be at different levels. Geometric updates could include the addition of new aerial surveys or higher resolution data to capture changes in the built environment such as new constructions or building modifications. The semantic updates may be improved estimates of material properties, insulation levels or system efficiencies. The dynamic update in the EDT system is also important. Real time or near real time data from sensors, smart meters or building management systems can be integrated to calibrate and validate the simulation results. This process is often referred to as model calibration and helps to reduce the discrepancies between the simulated and the observed performance. The input parameters are tuned to the measured data to make EDT more representative of the real conditions.

The update procedure is based on a feedback loop in which the output of the simulation is compared to the observed data. Differences are analysed for sources of error, e.g. incorrect assumptions about building usage or material properties. The model parameters are adjusted based on this analysis and the simulation is rerun. This iterative process increases the reliability of the EDT. Along with that, the EDT system allows the user to perform scenario analysis, testing different interventions (e.g. retrofitting measures, changes in glazing properties, installation of photovoltaic systems). This modelling framework can be used to assess these scenarios, providing a consistent basis for comparison. Thus, the EDT is not only a monitoring tool but also a decision-support system for sustainable building design and management.

4.1.1 Inputs and parameters required for windows energy modelling

Accurate representation of windows is essential for building energy simulation due to their significant impact on heat gain, heat loss, natural ventilation, and daylighting. Window energy modelling in EnergyPlus needs accurate input data from several areas of the building for windows energy modelling (Kohler et al., 2019; Lyons et al., 2010; Wijesuriya et al., 2025):

- 3D geometry (such as from point clouds or GIS/BIM models),
- Material properties (like glazing type, thickness, and U-value), and
- Environmental conditions (such as outdoor weather, solar radiation, and indoor temperature settings).

In EnergyPlus, windows are treated as boundary elements of the thermal envelope, influencing both zone-level and building-level energy performance. Therefore, correct modelling of windows requires a well-defined set of geometric, material, and environmental parameters. This section outlines the key inputs required for energy modelling of windows within EnergyPlus and how they interact with thermal and solar simulation algorithms. Firstly, The geometric inputs define the physical presence of windows in the simulation model which have been summarized in Table 6 below.

Table 6: Geometric inputs required for the windows energy modelling simulation with Energy Plus

Parameter	Description	Units
Width, Height	Window dimensions as extracted from building façade geometry	meters
X, Y, Z coordinates	Window placement with reference to the surface or zone	meters
Tilt and Azimuth	Orientation of the window surface in 3D space	degrees
Frame and Divider Info	Details of window frames and dividers that affect thermal bridging	--

Windows must be defined using specific material layers and optical properties that determine how they transmit or resist energy flow. These parameters are typically configured using the *WindowMaterial:Glazing* or

WindowMaterial:SimpleGlazingSystem object properties in IDF file for Energy Plus Simulation. Therefore, building glass and windows materials and some of the necessary optical properties must be considered for the simulations with Energy Plus which have been summarized in Table 7 below.

Table 7: Building material and optical inputs required for energy modelling with Energy Plus

Parameter	Description	Typical Values/Units
U-Factor	Overall heat transfer coefficient (inverse of thermal resistance)	W/m ² ·K
Solar Heat Gain Coefficient (SHGC)	Fraction of incident solar radiation admitted through the glazing	0.2 – 0.7 (dimensionless)
Visible Transmittance	Amount of visible light transmitted	0.3 – 0.9 (dimensionless)
Glass Thickness	Thickness of glazing layers	mm
Number of Panes	Single, double, or triple glazing	Integer
Gas Fill Type	Argon, Air, Krypton, etc.	Text

For precise energy modelling, external and internal environmental conditions affecting window performance must be considered which have been summarized in the table 8 below. These environmental variables are critical for heat balance calculations across the window surfaces and are incorporated using EnergyPlus weather files and schedule definitions. Most of these values can be obtained for the specific location EPW files available on weather portal.

Table 8: Environmental conditions inputs to be considered for energy modelling with EnergyPlus.

Parameter	Description	Source
External temperature	Outdoor air temperature affecting conduction and convection	Weather file (.EPW)
Solar radiation	Influences window heat gain and daylighting	Weather file (.EPW)
Wind speed and direction	Affects convective heat loss/gain and infiltration	Weather file (.EPW)

Shading systems influence energy performance by altering solar gains and daylight availability during occupied and unoccupied hours. Dynamic window performance also depends on shading strategies, which are simulated in EnergyPlus energy modelling using the following inputs presented in Table 9 below.

Table 9: Windows properties considered for the simulations with EnergyPlus.

Parameter	Description	Model Input Object
Overhangs/External shades	Fixed architectural elements that reduce solar gains	<i>Shading:Zone:Detailed</i>
Interior blinds or shades	Movable shading elements that can be scheduled or sensor-driven	<i>WindowShadingControl</i>
Glazing control strategies	Electrochromic, daylight-responsive tinting	<i>WindowShadingControl, Schedule</i>

4.1.2 Inputs and parameters required for rooftop energy modelling

Rooftop energy modelling involves estimating the potential for solar energy generation, thermal performance, and energy transfer through building envelopes (Middelhaue et al., 2021; Rayegan et al., 2024). For accurate results, a structured set of spatial, geometric, radiative, and environmental parameters is required. Geographic Information Systems (GIS) platforms, such as ArcGIS Pro and QGIS, together with tools like the Solar Radiation Tool and the SPAN (Solar Potential Analysis) plugin, provide comprehensive environments for processing, analysing and simulating rooftop energy performance. The conceptual framework for rooftop energy modelling is based on three basic components (Cavadini & Cook, 2021; Lucchi et al., 2020; Tiwari et al., 2020):

- geometric inputs derived from 3D data sources.
- environmental and radiative parameters
- building-energy specific attributes

Each component is essential for ensuring that simulations reflect realistic solar gains, shading losses, and rooftop suitability. Accurate 3D representation of building rooftops is foundational. This includes data from the point clouds, Digital Surface Models (DSMs) or other sources. Some of the essential geometric

properties to be considered for rooftop energy modelling are summarized in Table 10 below.

Table 10: Geometric properties to be considered for rooftop energy modelling.

Parameter	Description	Required usage / purpose
Roof orientation	Azimuth angle of roof surface	Solar panel alignment, irradiation modelling
Roof slope/tilt	Angle of inclination of the surface	Solar gain calculation
Roof area	Surface area of individual roof segments	Energy yield estimation
Roof obstructions	Chimneys, HVAC units, and dormers	Shading analysis
Surface roughness	Surface irregularity metrics	Diffuse radiation estimation

Like the windows energy modelling, Environmental conditions significantly impact rooftop energy performance be it with any software or modelling solution used for this purpose. These environmental conditions are sourced from regional weather files (e.g., TMY, EPW) or modeled directly in ArcGIS pro or the solution employed. In ArcGIS Pro, the Solar Radiation toolset integrates DSMs and irradiation models to compute solar insolation values. Similarly, the SPAN plugin in QGIS uses solar path algorithms and terrain data for hourly or annual solar energy estimation. Some of the important environmental conditions' parameters are summarized in the Table 11 below.

Table 11: Environmental conditions parameters considered for rooftop energy modelling.

Parameter	Description	Source
Global horizontal irradiance (GHI)	Total incoming solar radiation on a horizontal surface	Weather files, satellite-derived data
Direct normal irradiance (DNI)	Direct beam solar radiation per unit area	Solar radiation models in GIS
Diffuse horizontal irradiance (DHI)	Scattered solar radiation on horizontal surface	Meteorological databases
Albedo (surface reflectance)	Ground or surrounding surface reflectivity	Land cover classification layers
Temperature and wind speed	Climatic conditions influencing system efficiency	Weather stations or reanalysis datasets

Beyond geometry and environment, rooftop energy modelling must incorporate structural and temporal attributes of buildings. These attributes are typically retrieved from cadastral databases, municipal building registries, or urban energy maps. In ArcGIS Pro, this information is attached as attribute tables to building footprint layers. In QGIS, attribute joins and SPAN-compatible layers allow similar enrichment. Some of the important building properties which can be used are summarized in the Table 12 below.

Table 12: Structural and temporal attributes of buildings which can be considered for energy modelling.

Attribute	Description	Purpose in Energy Modelling	Possible source of the data
Year of construction	Indicates building design standards and insulation	Retrofit potential, degradation factor	Geoportal
Building use type	Residential, commercial, institutional, etc.	Load profile estimation	Geoportal
Energy rating/class	Classification based on energy performance	Baseline energy consumption	Geoportal
Occupancy data	Number of residents or users	Demand-side energy modelling	Geoportal
Material properties	Roof insulation, absorptivity, emissivity	Heat transfer calculations	Generalised material variations

Both ArcGIS Pro and QGIS have comprehensive rooftop energy modelling capabilities. ArcGIS Pro does well with integrated 3D modelling and raster-based solar analysis, while QGIS is more open and scriptable, especially with SPAN and GRASS plugins. The synergy of these tools enables multi-scale simulations of rooftop-to-district-scale energy scenarios. The datasets and their respective usage presented in the Table 13 below were employed for the solar potential estimation in this step.

Table 13: Datasets, their sources and usage for rooftop energy modelling.

Dataset/ Tool	Source	Usage
Photogrammetry point cloud	Aerial camera sensor	For rooftop detection
Digital Surface Model (DSM)	Photogrammetric point cloud processing	For Solar Potential estimation
Building footprints	Open Street Map (OSM)	Masking of building roofs
Agisoft MetaShape	Processing of Camera Images	Generation of photogrammetric point cloud
Cloud Compare	Cloud Compare	Data exploration and building orientation analysis
Area Solar Radiation Tool	ArcGIS Pro	Solar Potential Estimation

4.2 System Architecture for the development of an EDT system

The system architecture proposed for this research is structured into five tiers to bridge the gaps identified in current literature regarding data integration and building performance. This framework provides a logical path from raw data collection to a functional digital twin, ensuring that each step adds the necessary detail for accurate energy simulation.

The framework is based on the Data Sources and Inputs layer that integrates three types of data: high resolution aerial images, local temperature data and material properties like U-values. This architecture includes these inputs from the very beginning, thus taking into account the physical structure and the environmental context. This solves a common problem in the current literature, where material and geometry data are typically stored in separate and unrelated formats. 2. Geospatial Data Processing: The data collected is converted to 3D from 2D using photogrammetry. This stage generates a dense point cloud which characterises the external structure of the building. A key part of this phase is the application of the noise and outlier filtration. In empirical research raw-data from drones or satellites typically suffers from inaccuracies due to lighting conditions or sensor noise. At this point, it is important to remove these so that the final energy calculations are accurate and reliable. The third layer, Feature Analysis and Persistence, translates the raw 3D points into identifiable building features.

The system identifies features such as rooftops, windows and walls, and pulls out the specific geometry needed for energy modelling such as tilt, orientation and window-to-wall ratio. The architecture employs a structured database that stores these results, so the “digital” half of the twin contains all the semantic data needed to describe a real building and not just a simple shape.

In the Energy Simulation and Modelling stage, these building parameters are then paired with climate data to test performance. The system converts the data to industry standard formats such as IDF or gbXML for use with professional simulation engines. This layer calculates the heat loss of the building and/or solar gain over a period of time. With this physics-based approach, the model can be used as a ‘twin’ to predict how the building will perform under varying weather conditions.

Finally, all these processes come together in the Integrated EDT System. This portal serves as a central hub where the researcher can see the building through a 3D visualizer and monitor performance metrics on a dashboard. By connecting everything from the initial drone flight to the final simulation results, this architecture offers a coherent way to manage building energy data, solving the problem of fragmented workflows found in previous studies. Figure 10 below presents the system architecture for the development of an EDT system which can aid the planning of sustainable and energy efficient urban environments.



Figure 10: System architecture for the development of an operational EDT in built environment.

4.3 Methodology Workflow adopted in this research

The methodology for developing the Energy Digital Twin (EDT) is based on a structured workflow that integrates geospatial data processing, computer vision techniques, and energy simulation. The process begins with the acquisition of aerial imagery, which is processed using photogrammetric techniques in Agisoft Metashape to generate a dense three-dimensional point cloud. This point cloud serves as the primary geometric dataset representing the built environment.

The generated point cloud is first subjected to pre-processing steps, including noise removal, outlier filtering, and ground separation using height thresholds and surface normal analysis. This ensures that only relevant building structures are retained for further analysis. Subsequently, façade and rooftop regions are identified by analyzing surface orientation, enabling the isolation of vertical and horizontal building components.

The feature extraction is performed using machine learning and deep learning methods, including Random Forest, LightGBM, XGBoost, and KPConv. These models classify point cloud data into semantic classes including rooftops, windows, and non-building parts. Among these, KPConv shows higher accuracy on complex features, while ensemble methods provide computational efficiency.

After classification, region growing algorithms are applied to segment individual window cluster. Then, planar fitting methods like RANSAC are used to improve these segments and produce clean geometric representations. The features extracted from windows are vectorised in polygons, where geometric parameters such as area, orientation, tilt and position can be calculated. Window geometries are related to facade surfaces to derive additional attributes such as window-to-wall ratios.

The final task is to integrate these geometric and semantic inputs into EnergyPlus. The extracted features are converted to formats from which simulations can be performed with assignment of thermal properties such as U-value and Solar Heat Gain Coefficient. Energy simulations are then performed to estimate solar gains, heat losses and temperature dynamics, which is the basis of the Energy Digital Twin. Figure 11 below shows the overview of the end-to-end research methodology workflow.

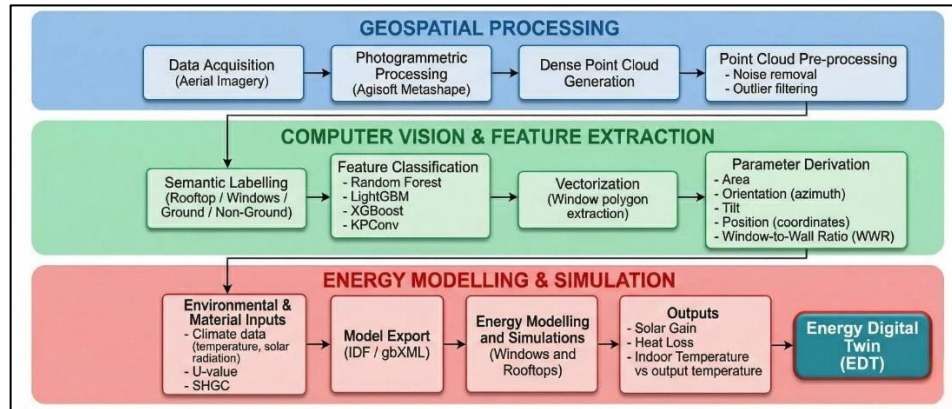


Figure 11 : Workflow for the building of EDT

The development of an Energy Digital Twin (EDT) begins with a rigorous geospatial data pipeline centered on aerial photogrammetry. High-resolution imagery is initially ingested into Structure-from-Motion (SfM) algorithms to generate a georeferenced dense point cloud. Because raw point clouds contain inherent sensor noise and environmental interference, the data undergoes systematic pre-processing. This involves the application of Statistical Outlier Removal (SOR) and ground separation filters to isolate building geometries from the surrounding terrain and vegetation, thereby establishing a clean foundation for high-precision surface analysis.

Building upon this refined dataset, the methodology employs a hierarchical classification strategy to differentiate between horizontal rooftops and vertical façades. Advanced machine learning architectures, including ensemble methods such as Random Forest and XGBoost alongside deep learning Kernel Point Convolutions (KPConv), are deployed for semantic labelling. This step enables the automatic recognition of different building elements, separating, for example, opaque wall areas from glazed openings. To refine these features, windows are segmented using region growing algorithms and then processed by RANSAC for accurate planar fitting and geometric surface refinement. By vectorisation, irregular segments are transformed into clean, closed polygons representing window boundaries, moving from discrete point clusters to analytical models. These vectorised geometries are then used to algorithmically derive critical spatial parameters such as surface area, azimuth (orientation), tilt and Window-to-Wall Ratio (WWR). These derived parameters act as the geometric backbone of the energy model, providing the necessary spatial context for the subsequent thermal

calculations and ensuring that the digital representation is consistent with the physical reality of the urban environment.

The conclusion stage merges these geometric insights with environmental and material metadata for physics-based simulation. The reconstructed surfaces are appended with external data such as Typical Meteorological Year (TMY) climate files and material specifications such as U-values and Solar Heat Gain Coefficients (SHGC). The model is exported into the EnergyPlus simulation engine in gbXML or IDF formats including shading and context modelling to consider mutual shading between buildings. The resulting outputs (solar gain, heat loss and indoor operative temperatures) are integrated back into the 3D framework to form a functional Energy Digital Twin that can be used for real-time predictive performance analysis.

4.4 Implementation for the EDT development

4.4.1 Geospatial Data selection

Energy digital twins for sustainable built environments rely heavily on geospatial data availability, quality, and their applicability to the energy use case. The selection of appropriate geographic datasets for the specific use case of a digital twin is thus an important stage, as it has a direct impact on the accuracy, scalability, and dependability of the resultant solution.

For urban energy modelling, several types of geospatial data can be accessed, including satellite images, airborne data (aerial photogrammetry and LiDAR), ground-based surveys, building information models (BIM) and existing GIS datasets. The different data sources have varying strengths and weaknesses in terms of spatial resolution, temporal frequency, accessibility, and cost. Satellite photography has wide coverage and frequent revisit and is suitable for large area surveillance. In practice, however, even commercial high-resolution data are often not spatially resolved enough to undertake extensive building-level energy analyses. It also suffers from limited ability to accurately capture vertical structures due to occlusions and narrow viewing angles. However, LiDAR data is very accurate in three dimensions, especially in terms of recording elevation and surface geometry. Airborne LiDAR systems can generate dense point clouds and can be utilised for terrain modelling and building extraction. Despite its excellent geometric precision, LiDAR data is typically expensive to acquire, process and derive a valid 3D model, and may lack the precise texture information needed for

building energy modelling and surface characterisation. Surface parameters such as material reflectance and thermal behaviour are significant in energy modelling, but they cannot be obtained directly from LiDAR datasets.

Ground-based surveys and mobile mapping technologies provide extremely high-resolution data and extensive information on building facades and materials. But, these procedures are time-consuming, labour-intensive and have limited spatial coverage. They are often more suitable for localised investigations than for city-scale applications. BIM data contains rich semantic and structural information of buildings, such as building materials and energy systems. However, BIM databases are rarely available for whole cities and often do not fit together well when they are assembled from different sources. Under these circumstances aerial photogrammetry is a balanced and feasible solution for the production of high resolution three-dimensional urban information. Aerial photogrammetry is the process of taking overlapping photographs of the earth's surface from cameras mounted on aircraft or unmanned aerial vehicles (UAVs). Photogrammetric processing of these images provides the production of dense point clouds, digital surface models (DSMs), orthophotos and textured 3D models. The method gives both geometric and radiometric data, which is required for energy-related assessments such solar potential estimation, façade orientation, and surface material assessment.

The use of aerial photogrammetry for this study is based on many significant benefits. First, it provides high spatial resolution, often in the range of a few centimetres to decimetres, allowing for precise representation of architectural shapes. Second, it detects texture information using RGB pictures, which is useful for detecting building materials and conditions. Third, it allows for more flexible data collection, including focused surveys of specific areas of interest. Finally, developments in photogrammetric software and computational power have made large-scale dataset processing more efficient and accessible.

4.4.2 Geospatial dataset Processing

For this research, a sequential photogrammetric workflow is proposed to transform raw aerial imagery into high-fidelity 3D dense point clouds. The objective of this procedure is to generate spatial data that is sufficiently accurate for the derivation of some building attributes necessary to conduct energy simulations. The core processing engine of the framework is integrated with Agisoft Metashape, which is chosen because of its proven robustness and

accuracy in scientific applications, where the geometric accuracy is essential for the further modelling. The proposed methodology begins with a rigorous and precise image acquisition strategy. The workflow assumes a high level of image redundancy to achieve accurate feature matching and triangulation, with 80% frontal and 60% side overlap. This guarantees that the whole point of the target terrain is observed from several different angles, a fundamental prerequisite for the 3D reconstruction reliability needed to create a valid Energy Digital Twin. The acquisition phase, described in more detail in Chapter 4, sets the baseline data quality for the entire proposed pipeline.

The methodology for processing aerial imagery proposed here begins with a rigorous pre-processing phase to maintain fidelity of the raw data. The first phase involves importing photos into the photogrammetric environment and performing a quality assessment to identify and cull blurry, overexposed or otherwise compromised frames. This step verifies the sufficient overlap between the consecutive images. If the visual sequence is discontinuous, the reconstruction would be affected. Once the dataset is structured and sanitised, the procedure moves to the picture alignment phase with Structure-from-Motion (SfM) techniques. In this process, the relative position and orientation of the camera in each position is recovered using essential visual elements of overlapping photographs.

This alignment step is concluded with the generation of a sparse point cloud representing the initial skeleton of the whole scene. The accuracy of this stitched representation is highly dependent on the image quality, percentage of overlap and the natural texture of the surfaces being captured. This sparse model is the fundamental geometric structure upon which more detailed dense point clouds are constructed. This sequential approach enables researchers to control a pipeline that converts individual aerial captures into a consistent 3D environment suitable for high-level building attribute extraction and subsequent energy modelling.

After generating the sparse point cloud, it was optimised with a method known as bundle adjustment. In this step reprojection error is reduced and camera parameters and point coordinates are improved. This stage also used image orientations and acquisition angles to ensure that the output was in a defined coordinate system. Then, after optimisation, the method continues with dense point cloud formation. Metashape reconstructs the scene with multi-view stereo (MVS) to get a dense one. The dense point cloud has a much larger number of points than the sparse point cloud, which helps it to capture fine details such as

edges of buildings, roof structures and surfaces. The processing settings can tune the density and quality of the point cloud to balance accuracy and computational costs.

The dense point cloud is used to generate a digital surface model (DSM) and a digital terrain model (DTM). The DSM is the elevation of all surfaces including buildings, plants, etc., while the DTM is the elevation of the bare ground surface. These models are fundamental for energy analysis, particularly for the determination of solar radiation dispersion and the influence of the terrain. The final step of the processing is to export the resulting datasets in formats that can be imported into GIS platforms and energy simulation programs. Common outputs are point clouds (LAS/LAZ) and raster models DSM and DTM (GeoTIFF). These records are then used to create energy digital twins that combine geometric information with other attributes such as building utilisation, material properties and energy consumption statistics. This operation involves a significant amount of cleaning and classifying data. Photogrammetric processing results may include noise and excessive features. In this phase, the noise and outliers were eliminated by the noise and SOR filters of cloudcompare software to prepare an error-free point cloud for the subsequent steps.

Aerial photogrammetry point clouds, as the major geospatial data source, provide a comprehensive and effective method for producing high-resolution, three-dimensional urban data. Its capacity to record both geometric and radiometric data makes it ideal for energy digital twin creation. Agisoft Metashape's processing procedure ensures that raw aerial photos are turned into precise and detailed models suitable for advanced energy evaluations. By combining these datasets with additional information, it is feasible to develop strong digital twins that help with the design and management of sustainable built environments.

4.4.3 Procedures for windows and rooftop features extraction from the point cloud datasets

Following the preprocessing of aerial photogrammetry-derived point clouds, advanced computer vision methods based on machine learning (ML) and deep learning (DL) are applied for feature extraction. The objective of this stage is to identify and classify key building components, particularly rooftops and windows, which are essential for the development of energy digital twins. These features have a direct impact on the energy behaviour of the building, such as solar gains,

heat losses and ventilation characteristics. For the classification models, the main input is the processed point clouds, already georeferenced and cleaned. A combination of traditional machine learning algorithms and deep learning methods is utilised in this study to achieve robustness and accuracy. We conduct point-wise classification with Random Forest, LightGBM, XGBoost, and Kernel Point Convolution (KPConv) models.

In our work, Random Forest algorithm have been used as a baseline supervised learning algorithm, since it is able to handle high dimensional data and is robust to noise. It is based on building many decision trees at training time and outputting the class that is the mode of the classes output by individual trees. For point cloud classification, the input features are geometric and radiometric features such as height, normal vectors, intensity values, and local surface variation. Random Forest is a good option for initial classification tasks as it provides stable performance and interpretable results.

Gradient boosting frameworks, such as LightGBM and XGBoost, were employed in the present study to achieve better classification accuracy and computational efficiency. These models are very useful in dealing with large scale data and complex feature interactions. LightGBM grow tree leaf-wise . Faster than level-wise tree growing . Better accuracy . XGBoost has regularisation methods that help in avoiding overfitting. Both methods are trained on labelled point cloud samples where each point is labelled with a class such as building, non-building, rooftop and window. Together, these models allow for a comparative evaluation and selection of the best performing classification.

Conventional machine learning models depend on hand-crafted features, but deep learning approaches like KPConv are more advanced and can directly learn spatial patterns from raw point clouds. KPConv is designed for irregular, unstructured point cloud data, and therefore is well suited for three-dimensional datasets of urban environments. It performs convolutions in a spatially consistent manner, using kernel points that are distributed in the local neighbourhood of each point. This allows the model to learn local geometric structures as well as contextual information without explicit feature engineering .

The KPConv model is trained on labelled data sets to classify every point into predefined categories. Its capability to learn hierarchical features enables a more precise detection of complex structures such as windows embedded in facades, or different rooftop geometries. Compared to traditional methods, KPConv

demonstrates improved performance in capturing fine details and distinguishing between closely related classes. The classified labelled point cloud is segmented into meaningful regions corresponding to the rooftops and windows. Then, the segmentation is used to perform the geometric reconstruction with region growing algorithms and planar fitting techniques. Methods based on region growing group neighbouring points based on a similarity measure, such as normal direction, curvature and spatial proximity. This enables to detect continuous surfaces which are crucial for the definition of building components. Then, these segmented regions are approximated as geometric primitives with the planar fitting techniques. Planar surfaces are fitted to the rooftops to represent different roof sections, capturing the orientation, slope and extent. For windows, we extract planar segments from facade regions to accurately describe their shape and position. These steps turn raw point clusters into well-structured geometric objects which can be further processed and analysed.

Then, the extracted features are vectorised to polygonal representations. The roof top polygons are used to compute parameters such as surface area, inclination angle and orientation with respect to the sun. These parameters are necessary for the evaluation of solar radiation and for the estimation of the potential of photovoltaic installations. The size, distribution and proportion of window polygons with respect to wall surfaces are analysed, which affect daylighting and thermal performance. Additional semantic attributes are assigned to enhance the usability of these features in energy modelling. For windows, attributes such as glazing ratio, shading factor and estimated thermal properties are included upon geometric characteristics and empirical assumptions. The orientation and surrounding obstructions of the rooftop surfaces enrich their solar exposure metrics. Such semantic enrichment is a way to transform purely geometric data into information directly usable for energy simulations.

The last step is to export the processed and improved features in formats that are compatible with building simulation tools. The common formats are gbXML and IDF and are extensively used in simulation systems, such as EnergyPlus. These formats allow to integrate geometric and semantic data in simulation workflows, enabling a comprehensive analysis of the building energy performance. The work uses machine learning and deep learning techniques for accurate and scalable extraction of building features from point clouds. The approach combines traditional and advanced methods through the combination of Random Forest, LightGBM, XGBoost and KPConv models. The extracted features, such as detailed representations of roofs and windows, are an important

part of the energy digital twin enabling high-resolution, performance-driven simulations of the built environment.

4.4.3.1 Deep Learning based KPConv model for building feature extraction from the aerial photogrammetry point cloud

Unlike 2D image-based or structured voxel-grid-based models, KPConv is designed to operate directly on raw, unordered point clouds. It introduces a deformable convolution operator capable of capturing local and contextual geometric information in a continuous 3D space. This approach eliminates the need for resampling or rasterization, which often causes loss of detail or misalignment in fine façade features like window frames and roof ridges. The implementation workflow has been adopted from (Thomas, 2019)

Traditional convolutional neural networks (CNNs) are not well-suited to non-Euclidean data structures like point clouds due to their reliance on regular grid formats. KPConv overcomes this by learning weights associated with kernel points distributed in the local neighbourhood of each point, effectively simulating convolution in the unstructured domain (L. Chen & others, 2019; Guo & others, 2020). This makes it highly suitable for the identification of architectural features where spatial relations and local surface characteristics are essential.

The input point cloud data used in this research consists of aerial photogrammetry point cloud. A pre-processing pipeline is implemented to enhance data quality, which includes:

- Noise removal using statistical outlier filtering.
- Down sampling with voxel grid filtering to ensure computational efficiency.
- Normal vector estimation using PCA over local neighbourhoods.

Feature computation, including height above ground, intensity, curvature, and planarity metrics. These features are encoded alongside the XYZ coordinates and fed into the KPConv network as input descriptors (Boulch & others, 2020; Thomas & others, 2019). The model is further improved to distinguish between windows and rooftops and surrounding elements like walls, balconies, and chimneys, as these have specific geometric signatures such as flatness, reflectivity, angular orientation and the presence of such auxiliary features. In this work, the KPConv architecture makes use of a hierarchical feature extraction strategy akin to PointNet++ but replaces pointwise MLPs with convolutional layers defined on

kernel point neighbourhoods. The architecture consists of the following components:

- Input Layer: Accepts $N \times F$ input tensor, where N is the number of points and F is the number of input features.
- Convolutional Blocks: Each block applies a KPConv operation followed by batch normalization and ReLU activation.
- Pooling Layers: Subsample the point cloud while aggregating contextual information, enabling multiscale feature representation.
- Fully Connected Layers: At the final stage, a series of MLP layers perform classification of each point into window, rooftop, or non-relevant class.

We adopt a supervised learning approach where manually annotated point clouds are used as the ground truth for training the model. Labels are given at point level using a custom annotation tool developed for this purpose, which allows the user to visually assign window and rooftop classes with a high spatial precision. The loss function used is cross-entropy loss with class weighting to counter data imbalance especially as windows are typically less points than walls or roofs. The dataset is split into training, validation, and test sets using a spatial tiling method to ensure that scenes in each set are geographically independent. Data augmentation techniques such as random rotations, jittering, and scaling are applied to improve model generalization across different building typologies.

Model performance is evaluated using metrics tailored for semantic segmentation tasks, including:

- Overall Accuracy (OA)
- Mean Intersection over Union (mIoU)
- Precision, Recall, and F1-score for window and rooftop classes

Post-classification, the segmented windows and rooftops are extracted and vectorized using region-growing algorithms and planar fitting techniques. This step allows the creation of geometric primitives suitable for downstream use in building simulation environments like EnergyPlus. The extracted window polygons are further enriched with semantic information (e.g., estimated glazing ratio, shading factor), while rooftop surfaces are used to derive solar exposure, inclination, and potential PV panel areas.

These refined features are then exported to a simulation-compatible formats such as IDF, forming the core input for the Energy simulations for an EDT system. By ensuring accurate spatial and semantic representation of windows and rooftops, this KPConv-based pipeline enables high-resolution, performance-driven simulations of building energy dynamics.

4.4.3.2 Machine learning based XgBoost model for the feature extraction from the aerial photogrammetry point cloud

XGBoost is a gradient-boosted decision tree model, for the classification and can be employed for the extraction of windows and rooftop segments from raw 3D point cloud datasets. Raw point clouds are typically unstructured, making them unsuitable for traditional grid-based classification approaches. Instead, point-level features must be derived, and a model capable of handling non-linear relationships, large data volumes, and sparse input must be employed. XGBoost is an appropriate tool in this context due to its efficiency, scalability, and ability to handle structured and semi-structured tabular data created from pre-processed point clouds. The implementation workflow has been adopted from (T. Chen & Guestrin, 2016; GitHub, 2019)

The generation of reliable Energy Digital Twins (EDTs) for building-level simulation requires accurate identification and classification of building envelope components such as rooftops and windows. These characteristics directly affect energy exchange processes, such as the absorption of solar radiation, heat loss, ventilation and daylight penetration. However, extraction of these components from point cloud datasets poses significant technical challenges such as occlusion, noise, varying density of points, and similarity of surface patterns in façades. In this work, we present the application of XGBoost, a gradient-boosted decision tree model, to classify and extract windows and rooftop segments from raw 3D point cloud data.

In point clouds, the primary attributes are X, Y,Z coordinates of the point clouds with the additional attributes such as intensity (reflectance), colour values (RGB), and scan angle are also included. For feature extraction purposes, each point must be assigned a semantic label such as "window", "roof", "non ground", or "ground" based on its geometric and radiometric properties.

Raw point clouds are typically unstructured, making them unsuitable for traditional grid-based classification approaches. Instead, point-level features need to be extracted and a model capable of handling non-linear relationships, high

data volumes and sparse input has to be used. In this context, XGBoost is a suitable tool for its efficiency and scalability, and its ability to handle structured and semi-structured tabular data that is generated from pre-processed point clouds. To apply XGBoost for classification, the raw point cloud has to be converted into a structured dataset of features. These features can be grouped into three main categories:

1. Geometric Features:

- Coordinates (X, Y, Z) of each point.
- Normal vectors indicating the orientation of the local surface.
- Planarity, curvature, roughness, and sphericity calculated within a local neighbourhood using Principal Component Analysis (PCA).
- Distance to ground, which is critical in distinguishing roofs from walls and windows.

2. Radiometric Features:

- Intensity (reflectance values) which can help differentiate between glass, metal, and other surface materials.
- RGB values, where available, can enhance the detection of common façade materials.

3. Contextual Features:

- Density of neighbouring points.
- Height variation within a local neighbourhood.
- Vertical and horizontal point distribution statistics.

These features are computed for every point using a fixed-radius or k-nearest neighbours (k-NN) search and form the input variables for the XGBoost model. XGBoost is based on decision tree ensembles built through a boosting technique. Boosting is a sequential learning process in which each tree attempts to correct the errors made by the previous one. Unlike traditional decision trees, XGBoost employs:

- Gradient-based optimisation: It uses second-order gradient information to optimise a loss function (e.g. SoftMax or logistic loss for classification).

- Regularisation: XGBoost includes L1 and L2 regularisation terms which penalise complex trees and reduce overfitting.
- Parallel tree construction : To speed up the training, XGBoost constructs trees in parallel.
- Tree pruning is used to remove branches with little contribution to the final result
- Post-pruning techniques are used to improve model generalisation .

The model is trained on labelled datasets, where each point is designated with its corresponding class: “window”, “roof” or “other”. A stratified sampling strategy is used to maintain class balance due to the relative sparsity of window points compared to walls or roofs. Once trained, the XGBoost classifier assigns a label to each point in the test dataset. For rooftop detection, the model relies heavily on:

- Elevated position from the ground.
- High planarity.
- Low vertical variation.
- Specific surface angles (e.g., inclined roof planes vs. flat terraces).

For window detection, the XgBoost model focuses on:

- Flat vertical surfaces.
- Mid-height façade locations.
- Reflective intensity signatures (often lower for glass).
- Geometric discontinuities between walls and openings.

The output is a point-wise classification map, where connected components of “roof” or “window” points are further processed using clustering and surface fitting techniques to form regularized geometric shapes suitable for export into energy simulation formats (e.g., gbXML or IDF).

To evaluate model performance, standard classification metrics such as accuracy, precision, recall, and F1-score are computed for each class. Due to the high imbalance in class distribution (especially in urban scenes), precision-recall curves are also analysed. The Post-processing steps involve:

- Outlier removal: Isolated misclassified points are filtered using majority-vote smoothing in a local neighbourhood.

- Geometry reconstruction: Classified point clusters are converted into 3D polygons using RANSAC-based plane fitting or alpha shapes.
- Topology correction: The gaps between adjacent surfaces, e.g. between wall and window, are closed according to architectural constraints and energy modelling needs.

XgBoost: A Technically Sound and Efficient Classifier to Extract Rooftop and Window Features from Point Clouds Its structured learning framework, capability to deal with a variety of input features and excellent generalisation ability make it appropriate for integration in Energy Digital Twin pipelines for building performance simulation. The use of XgBoost is suitable for urban scale data classification for the following advantages:

- It handles high-dimensional feature vectors efficiently.
- It is robust to missing or noisy features, which is common in LiDAR datasets.
- It provides interpretability through feature importance scores, helping understand which geometric or contextual features are most influential in classification.
- It can be trained quickly even on large point cloud datasets, making it suitable for urban-scale applications.

4.4.3.3 Machine learning based LightGBM model for the feature extraction from the aerial photogrammetry point cloud

Another effective approach to building feature extraction is the application of the LightGBM (Light Gradient Boosting Machine) model. LightGBM is a gradient boosting framework that has gained popularity for classification tasks due to its high efficiency and speed, especially when dealing with large datasets like point clouds. It uses a decision tree-based algorithm and employs histogram-based techniques to process the data faster and more effectively. This model can be used to classify points within a point cloud into meaningful building components such as windows, rooftops, walls, and doors, which can then be used in energy simulation models like EnergyPlus. The implementation workflow has been adopted from (GitHub, 2023; Ke et al., 2026)

LightGBM builds decision trees one after another, each tree attempting to correct the mistakes of the trees that preceded it. Unlike the traditional gradient boosting models, it grows trees in a leaf-wise fashion which may cause a deeper

tree and a better model accuracy. Furthermore, LightGBM uses a histogram-based method to find the best split for each node, which speeds up the training process and improves scalability to large datasets. This is especially useful when dealing with point cloud data containing millions of 3D points. The key advantages of LightGBM include:

- Ability to manage large-scale data efficiently.
- Optimisation of memory via histogram-based learning.
- Effective treatment of categorical features without one-hot encoding
- Parallel and distributed learning which speeds up processing especially for large point clouds.

For example, in the case of extracting features from point clouds, you could train LightGBM to recognise features of windows and rooftops from a list of features extracted from the point cloud. The first step to use LightGBM for extracting window and rooftop features is to process the raw point cloud data . Generally, point cloud data has x, y and z coordinates, colour and occasionally intensity. To prepare this data for classification, several feature extraction steps are necessary:

- **Point Normal Vectors:** Normal vectors describe the orientation of a surface at each point in the cloud. For windows and rooftops, these vectors help identify flat surfaces. Windows typically have smooth, flat surfaces, and rooftops often exhibit a more complex structure with slopes and ridges. Calculating the normal vectors helps differentiate between these surface types.
- **Point Density:** The spacing of points in a typical point cloud varies depending on the scanning method and the distance to the scanner. Because windows are vertical and often planar, they tend to display higher point density than adjacent wall segments. Depending on the structure, the point densities of rooftops could be used as features in the model.
- **Height and Elevation:** The z-coordinate of each point can be used to represent the relative height of surfaces. This is particularly useful for the separation of rooftops (which will have a higher elevation than windows) and for the detection of windows on lower levels of buildings. Height and elevation gradients can also be added as an input to the model for surface differentiation.
- **Geometrical Properties:** For rooftop extraction, properties such as the slope, aspect, and planarity of the surfaces are crucial. Windows, on the

other hand, are typically defined by flat, vertical surfaces with little to no slope.

- Once the point cloud data is pre-processed, relevant features must be engineered to serve as inputs to the LightGBM model. These features might include:
- Point Neighborhood Analysis: This includes analyzing the local point cloud neighborhood to determine if a point is part of a larger flat surface, which is a common feature of windows and rooftops.
- Reflectivity and Color: In some point cloud data, points are associated with colour or intensity values that can be used as features. Windows have a different reflective quality to the surrounding wall surfaces. The colour of points can help distinguish glass windows from other materials like brick or concrete.

After the feature extraction step, the LightGBM model is trained using labelled data. This requires hand annotated point cloud data where visible windows and rooftops are labelled. The training dataset will be composed of labelled 3D points and their relevant features like point normal vectors, density, elevation, etc. LightGBM will use these labelled points to learn the relationship between the extracted features and the target classes (windows or rooftops). The model builds decision trees, each split is based on the feature that minimises the classification error. The trained model can predict the class of unseen points in a new point cloud dataset.

After training the model on a set of validation data not used in training, the performance of the model is evaluated. The performance of the model is evaluated using metrics such as accuracy, precision, recall and F1-score. The results indicate the performance of the model in detection of the windows and rooftops as well as the ability of the model to distinguish the windows and rooftops from other parts of the building. After the classification, a post-processing is necessary to refine the extracted windows and rooftops. For instance, spatial smoothing can be applied to remove isolated misclassified points, geometrical fitting can be used to fit detected windows and rooftops into more defined shapes like rectangles or polygons, making them suitable for energy modelling tools.

The final extracted windows and rooftops can be incorporated into the models of the Energy Digital Twin. These features are used to simulate thermal performance, solar gain, shading and heat loss and improve the accuracy of energy simulations. Accurate models of rooftops and windows can be used to

simulate energy use, which can improve planning and optimisation of energy systems in buildings. LightGBM provides an efficient and scalable solution for the extraction of window and rooftop features from point clouds, which can be used to improve Energy Digital Twins. For this task, LightGBM is the best model as it can handle not only large-scale datasets, but also complex geometrical and contextual features. With proper data preparation, feature engineering, and model training, accurate building features can be extracted to drive more precise energy simulations, ultimately promoting sustainable building design and retrofitting strategies.

4.4.3.4 Machine learning based Random Forest model for the building feature extraction from the point cloud

The Random Forest model is an ensemble learning algorithm that builds multiple decision trees during training and aggregates their outputs to increase classification accuracy (Grilli, 2017). This takes place by randomly selecting a subset of the input features and data points for each tree in the forest . This prevents overfitting and ensures generalisation . The model operates by producing binary decision nodes from the most informative features like, for instance, the spatial coordinates, point density, or surface curvature. At each node, the decision tree splits the dataset based on a feature that maximizes the distinction between the classes (e.g., window vs. non-window). This results in many relatively simple decision trees that, when aggregated, lead to highly accurate and robust predictions. The implementation workflow has been adopted from (Breiman, 2001; Dong, 2020; Sun, 2021)

In the context of point cloud feature extraction, the Random Forest model can be particularly useful because it can handle the vast number of features present in 3D data without requiring prior assumptions about the data distribution or geometric properties of the surfaces. Before implementing the Random Forest model, it is essential to properly preprocess the point cloud data. Raw point clouds often contain noise, missing data, and occlusions, which can interfere with feature extraction. The following steps are typically involved in preprocessing:

- Down sampling: Point cloud datasets are typically very large, which makes their processing computationally expensive. The number of points is reduced using voxel grid filtering or other down sampling methods while keeping the general structure of the scene. This step greatly reduces the computational load and speeds up further processing.

- **Outlier Removal:** Point clouds are often noisy and have outliers that do not correspond to any part of the building. Statistical methods can be used to remove points that are far away from the majority of the data such as the statistical outlier removal filter.
- **Normal Vector Estimation:** For each point in the cloud a normal vector is computed in order to specify the orientation of the surface at that point. This is especially important for isolating flat surfaces such as windows and rooftops from irregular non-planar features.
- **Segmentation:** The next step is to segment the point cloud into different regions based on geometrical features such as surface smoothness or curvature. Flat surfaces can be windows and rooftops, while more complex surfaces can be walls or other building components. Segmentation helps to reduce the dimension of data set, and hence the relevant features for classification can be easily focused.
- **Feature Extraction:** Various geometric features are extracted from the segmented point cloud to train the Random Forest model. These features can include:
 - **Surface normals:** These provide information on the orientation of surfaces, which can help distinguish between vertical (walls) and horizontal (roofs) surfaces.
 - **Curvature:** This helps in identifying curved or slanted surfaces, such as those found in complex roof geometries.
 - **Height and spatial coordinates:** These are crucial for understanding the vertical and horizontal positioning of windows and rooftops in relation to the building structure.

After pre-processing the point cloud and extracting the relevant features, the Random Forest model is trained with the labelled data. During training, the model is trained on a set of point cloud data with manual annotated window and rooftop labels. These labels are the ground truth for the model to learn how to classify new unseen data of point clouds. The Random Forest algorithm creates a lot of decision trees. Each is trained on a random subset of data and features. At each tree node, the algorithm selects the most informative feature to split the data. The decision trees grow independently of one another, with each tree trained on

different aspects of the data. This randomness helps ensure that the model does not overfit the training data and performs well on new data. During testing, each tree votes on the classification of a given point, and the majority vote is taken as the final classification result.

For the specific task of window and rooftop extraction, the Random Forest model relies on the geometric features described earlier. These features allow the model to distinguish between different types of building surfaces:

- **Windows:** Windows are typically flat vertical surfaces that have more points around their edges. The window points' normal vectors will normally be aligned with the vertical direction of the building façade. Also, windows may have certain curvature properties that are different from walls or rooftops, particularly when detected from oblique angles.
- **Rooftops:** rooftops typically have horizontal surfaces that are quite sloped or curved, depending on the style of roof. Windows vary great deal in height and point density from rooftops. The spatial location of the roof (typically at the top of the building) can assist the model to distinguish it from other building features.

Finally, the Random Forest model is applied to a separate testing dataset to determine the accuracy of the model in extracting windows and rooftops. We assess the model's ability to correctly classify window and rooftop features while minimising false positives and false negatives using common metrics such as precision, recall and F1-score. Subsequently, the results are cleaned up by post-processing methods after the points are categorised to windows, rooftops or other building components. This can involve removing small, isolated points, or merging broken window segments to form continuous windows. The classified features are also associated with energy simulation models and incorporated into Energy Digital Twin models for energy performance analysis.

4.4 Energy Modelling from the building features extracted from the point clouds

Energy modelling plays a crucial role in evaluating the energy performance of buildings, particularly for Energy Digital Twins (EDTs), which simulate real-time energy consumption and efficiency. Inclusion of building features, such as windows and rooftops, extracted from point cloud data, in the energy modelling process is crucial for accurate results. Detailed geometrical information of

building components, which can be turned into digital models for energy simulations, is usually available in point clouds derived from LiDAR or photogrammetric techniques. Within this framework, after the feature extraction process concerning windows and rooftops, the integration of extracted features into energy simulation tools is followed. EnergyPlus is used for simulating the performance of windows, while ArcGIS and the QGIS plugin SPAN are used for rooftop energy modelling. Each building component requires specific inputs and parameters to ensure that the energy simulation accounts for factors like thermal performance, solar gain, and insulation properties.

4.4.1 Energy modelling procedure with windows

In EnergyPlus, window modelling is a key component of dynamic thermal simulation. Accurate modelling of windows is necessary in the Energy Digital Twins context to evaluate heating and cooling loads, solar gain and overall building performance for the city of Turin, Italy, with its temperate climate characterised by cold winters and warm summers (classified as Cfa/Cfb under Köppen).

The first step is to define the geometry of each window in EnergyPlus by using the object class *FenestrationSurface:Detailed* in the IDF file. Windows are always sub-surfaces to an opaque parent surface (normally wall). Each window has its vertices defined in world or relative coordinates. In the typical residential building of Turin, for example, windows are 1.2 m wide and 1.5 m high and are usually located on the south and west façades to maximise the solar gain in winter. Each window is embedded in a *BuildingSurface:Detailed* (generally an exterior wall) object. For example, a south-facing (0,0,0) to (10,0,0) wall may have three windows, symmetrically placed, with 2 m spacing. These window geometries can be extracted from the buildings either by photogrammetric point cloud segmentation using the procedures mentioned in sections above.

Window performance is defined by a layered construction using the Construction object referencing materials like *WindowMaterial:Glazing*. In the city of Turin, typical residential buildings employ double-glazed or low-e double-glazed units due to regional energy efficiency standards (*as per Italy's D.Lgs. 192/2005*). A typical construction definition for a double-glazed unit is:

- Outer layer: Clear glazing, thickness 0.006 m, solar transmittance = 0.75, U-value $\approx 2.8 \text{ W/m}^2\cdot\text{K}$

- Air gap: 0.012 m
- Inner layer: Low-E coated glazing, solar transmittance = 0.65, emissivity = 0.1
- Overall U-value: $\sim 1.6 \text{ W/m}^2\cdot\text{K}$, SHGC = 0.55

These materials are defined using the *WindowMaterial:Glazing* and *WindowMaterial:Gas* (e.g., Air or Argon) objects. The frame is also modelled using *WindowProperty:FrameAndDivider*, which for aluminum frames with thermal breaks has a frame U-value of approximately $3.5 \text{ W/m}^2\cdot\text{K}$.

EnergyPlus simulates shortwave solar radiation transmittance through windows using angle-of-incidence-dependent optical models. The *WindowShadingControl* object is used to account for dynamic shading systems, automated blinds or shutters are common in Turin's residential buildings. Typical operation might follow solar radiation thresholds: for example, blinds are closed when incident radiation exceeds 250 W/m^2 during the peak summer season in the month of June-August for an average peak of three months. External obstructions such as balconies, vegetation, or adjacent buildings are accounted for using *Shading:Site:Detailed*. For urban localities in Turin like San Salvario or Centro, shading from adjacent buildings is significant, especially on narrow streets. Obstructions are defined geometrically with vertices, and EnergyPlus performs a ray-tracing analysis to compute view factors and sun obstruction throughout the year.

The modelling of openable windows is done with the object class *ZoneVentilation:WindandStackOpenArea*. Natural ventilation is especially important in Turin during the spring and autumn. For example, an openable window of 1.8 m^2 can be characterised by a flow coefficient of 0.6 and an opening schedule from 08:00–18:00, from April to October. Stack and wind driven ventilation are calculated on the basis of height differentials and local weather data, for Torino an average wind speed of 2.5 m/s . EnergyPlus computes the internal gains coming from transmitted solar radiation (both convective and radiative). Zone heat balances are performed considering windows using the *SurfaceProperty:OtherSideConditionsModel,ZoneSurfaceHeatBalanceAlgorithm*. The model predicts solar heat gain, longwave radiative exchange and convective heat transfer from the inside window surface to the room air. These include interactions with thermal mass, zone air temperature and internal loads.

For example, in winter (December, January) the typical incident solar radiation on a south-facing window in Turin can be 300–400 W/m² at midday. The transmitted solar gain is ~165–220 W/m² for a SHGC of 0.55, which greatly offsets heating demand in passively designed buildings. The Key outputs configured using *Output:Variable* include:

- Surface Window Transmitted Solar Radiation
- Zone Windows Total Transmitted Solar Radiation
- Surface Inside Face Convection Heat Gain Rate
- Solar Heat Gain Coefficient through the windows
- Variations in the inside and outside temperatures
- Heat losses through the windows

These outputs provide hour-by-hour diagnostics that can be used to calibrate or update Energy Digital Twin models. For instance, discrepancies in predicted vs. measured window gains or losses can inform corrective adjustments to material properties or control schedules in the digital twin platform. Once the window components are modelled and simulated, the data can be synchronized with external building metadata including year of construction, energy class (e.g., Class D or E for pre-1990s buildings in Torino), occupancy levels, and façade orientation. These datasets allow contextualizing simulation results within broader energy modelling workflows at the district or urban scale.

4.4.2 Energy modelling procedure with rooftops

The rooftop energy modelling process begins with the acquisition of high-resolution spatial data:

- Digital Surface Models (DSMs): aerial photogrammetry-derived DSMs with a spatial resolution of 1 meter are obtained the processing of dense point clouds.
- Building Footprints: Vector data delineating building outlines are sourced from Open Street Map (OSM).
- Meteorological Data: Solar irradiance and climatic parameters are retrieved from the PVGIS database, providing long-term averages essential for accurate solar potential assessment.

In ArcGIS Pro, the following procedures are implemented for the energy modelling with the rooftops:

- Slope and Aspect Analysis: Using the 'Slope' and 'Aspect' tools, roof planes are classified based on inclination and orientation. Roof sections with slopes between 10° and 35° and south-facing aspects (135° to 225°) are considered optimal for PV installation.
- Solar Radiation Mapping: The 'Area Solar Radiation' tool calculates annual solar insolation, incorporating factors such as latitude, elevation, and shadowing from adjacent structures.

The next step in this procedure is the Photovoltaic Potential Estimation which is one of the essential components of an EDT development and primary purpose of the extraction of the rooftop from the point clouds. The potential for PV energy generation is estimated by:

- Energy Yield Estimation: Assuming a system efficiency of 15% and an annual insolation of 1,300 kWh/m² the anticipated annual energy production is:

$$\text{Annual PV Energy Output} = \text{Usable Area} \times \text{Insolation} \times \text{System Efficiency}$$

4.5 Geodatabase for EDTs and their functionality

The GeoDB serves as the main repository for 3D geospatial datasets, turning raw geometric points into structured, usable data. In this work, the physical features of building elements such as rooftops and windows extracted from aerial point cloud are stored. Each feature is stored as a single object having specific attributes like its precise area, slope and orientation. This geospatial data storage is critical, as it allows the digital twin to maintain a persistent link between the 3D model and the real-world coordinates. By using higher Levels of Detail (LoD), such as LoD3 for window features, the GeoDB provides the high-fidelity spatial data needed to account for complex urban factors like shading from neighbouring structures, which is essential for realistic modeling.

Beyond storing geometry, the GeoDB serves as a dynamic storage for the final energy simulation results, creating a complete feedback loop between the physical building and its performance. The simulation engine then calculates values like solar potential and thermal heat loss. The results are immediately written back into the database and associated with the respective building objects. This allows researchers to query specific datasets, such as finding all north-facing rooftops with a potential below 800 kWh/m². It is important to store the spatial

data and the performance metrics together, in order to allow accurate visualisation and decision making. However, it is important to recognize that managing such large, complex datasets requires a robust database structure to ensure that the digital twin remains fast and responsive when simulating entire city blocks.

4.5.1 Development of a Geodatabase for the development of an EDT system

The core of this approach is structured around CityGML and its standards for modeling urban environments. The methodology draws upon the ANSI/X3/SPARC standard of 1975, which outlines the essential modeling phases: external, conceptual, logical, and internal models. These phases direct the structuring of data from natural language descriptions of the application domain (external model) to implementation ready structures (internal model). The conceptual model of this project is represented in the Unified Modelling Language (UML) which is based on the definition of objects, their properties and relationships. In GeoDB, point clouds and meshes have been united for an accurate and dynamic spatial representation based on CityGML's Level of Detail (LoD) standards. This phase is about technical interoperability, i.e. data from different sources and formats (LiDAR, photogrammetry and other sensors) can be combined in the system without problems. Compliance with CityGML Version 3 standards ensures consistency and compatibility with future urban modelling efforts. During data integration, the point clouds and meshes are processed at different granularity levels to ensure that urban features are represented with high accuracy while being computationally efficient.

One of the first methodological steps is the data harmonisation of different semantically and geometrical datasets designed to develop a digital twin of an urban environment. The ANSI/X3/SPARC standard has outlined modelling phases since 1975, which include the external model (using natural language to describe the application domain), the conceptual model (independent of implementation, identifying concepts and relationships), the logical model (implementation-focused, translating the conceptual model into a computer-readable structure), and Internal model (the implementation). The Unified Modelling Language (UML) is commonly used for the conceptual model, emphasizing objects, properties, and relationships. Classes representing real-world objects (such as, in this case, Building footprints, roofs, windows, DSM, etc.) have attributes and are depicted in diagrams with associations indicating relationships.

This model undergoes simplification, formalization, and schematization for the spatial GeoDB development.

Some attributes are defined for classes that represent real-world urban objects such as building footprints, roofs, windows and digital surface models (DSM). UML diagrams are given to illustrate the classes. These diagrams are helpful to understand the relationship between objects and how they interact on the digital environment. The objects are simplified, formalised and schematised so that they correspond to the practical requirements of the spatial GeoDB (Geospatial Database). The next step is the migration from the conceptual and logical design towards the actual implementation of these spatial classes in the GIS GeoDB. The classes are instantiated and the relations among them which are important for the integrity of data and for spatial queries are defined in the GeoDB at this point.

After the conceptual and logical design, the spatial classes are implemented in a GIS GeoDB, and the relations are defined. Finally, point clouds and meshes have been added to the GeoDB according to the different Levels of detail of CityGML (LoD 3). In this task the technical interoperability approach is considered. A WebGIS platform will help the publication of web-based queries and will be of great utility to the stakeholders and will be of substantial help for urban planners, municipal offices and policy maker bodies. Generally, WebGIS platform is popular for their ease of use, which allows them to be easily navigated and interacted with. Besides, these platforms are able to supplement and update the database underneath, so that the information shown is always current and relevant to the users' needs. The use of WebGIS capabilities attempts to create a replicable methodology and a powerful tool for the analysis of spatial data and decision processes in different fields. One of the main features of the WebGIS platform is its flexibility. The platform also makes it possible to continuously enrich and update the database, so that the digital twin develops with the changes in the urban fabric. This dynamic functionality ensures that information is always up to date, making the platform an essential tool for urban planning and management in the long run. The platform is made responsive to human intervention and automated data streams, by integrating mechanisms for data updates and error rectification.

The schema shown in the figure 12 below defines a complete semantic framework for the multi-scale modelling of urban environments, organised through progressively complex Levels of Detail (LOD 0 to LOD 4). This hierarchy acts as a relational bridge from raw geospatial datasets like point clouds

and orthophotos to high-level analytical applications. By organising the urban fabric into discrete, connected entities, the model enables the transition from a macro level basic inventory management to a micro level deep component level analysis and performance simulation.

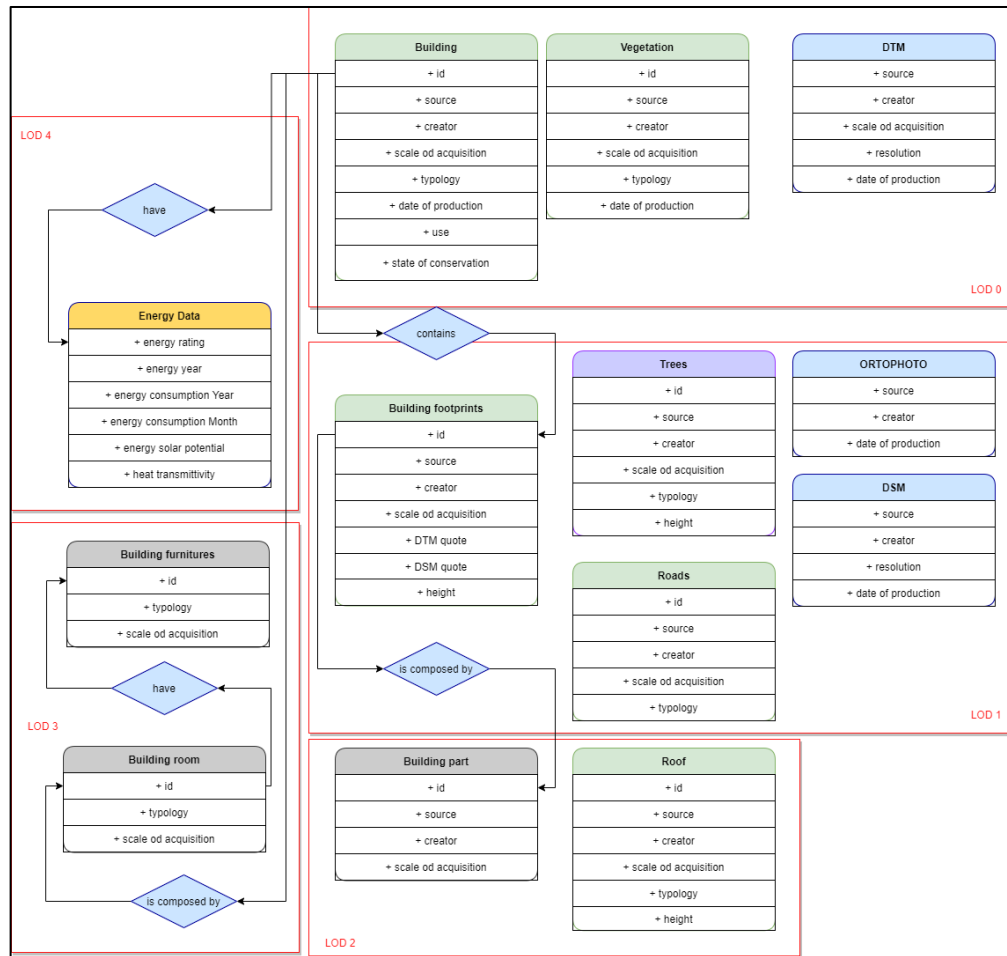


Figure 12: Conceptual Model for the GeoDB for the development of Torino EDTs, taken from (Yadav et al., 2024)

At the foundational levels, LOD 0 and LOD 1 define the administrative and volumetric context of the urban scene. LOD 0 focuses on metadata and typology for broad entities like buildings and vegetation, while LOD 1 introduces the third dimension through Digital Terrain Models (DTM) and Digital Surface Models (DSM). The "contains" relationship between these layers allows for the grounding of abstract building records into physical footprints. This stage is crucial for initial

site analysis, where the integration of orthophotos and terrain data provides the environmental baseline necessary for more advanced feature extraction.

Structural granularity is achieved at LOD 2 and LOD 3 where buildings are decomposed into parts. The “is composed by” relationship in LOD 2 is used to find special geometrical features such as roofs and building parts. This is the precise level where semantic segmentation algorithms such as KPConv or XGBoost models described above are applied to classify complex architectural elements from point cloud data. This logic is then taken further into the interior of the building with LOD 3, defining the interior partitions like rooms and furniture, translating the focus of the model from external GIS based topography to internal BIM scale architectural detail. Finally, LOD 4 represents the functional pinnacle of the framework, where physical geometry is enriched with dynamic performance metrics categorized under Energy Data. Through the "have" relationship, the model associates static building objects with vital attributes such as heat transmissivity, solar potential, and longitudinal energy consumption. This integration transforms the static 3D representation into a high-fidelity Urban Digital Twin. By correlating the specific orientation and geometry of a roof identified at LOD 2 with the energy ratings at LOD 4, researchers can conduct sophisticated simulations to optimize urban sustainability and energy efficiency at both the individual building and district scales.

Chapter 5

Study area, datasets acquisition systems and processing Tools

5.1 Study area

The study area undertaken for this research is the city of Torino, which is the 4th largest city in Italy, located in the Piedmont region. The experiments were conducted initially on the small test site and then scaled up to 2 different localities with approximately similar no. of buildings to analyze the variations in the energy patterns with the development of an EDT system. The localities considered for this research work are San Salvario locality and Sky Scraper locality near Porta Susa station in the city of Torino. The location of the study area and selected localities has been represented in the Figure 13 below.

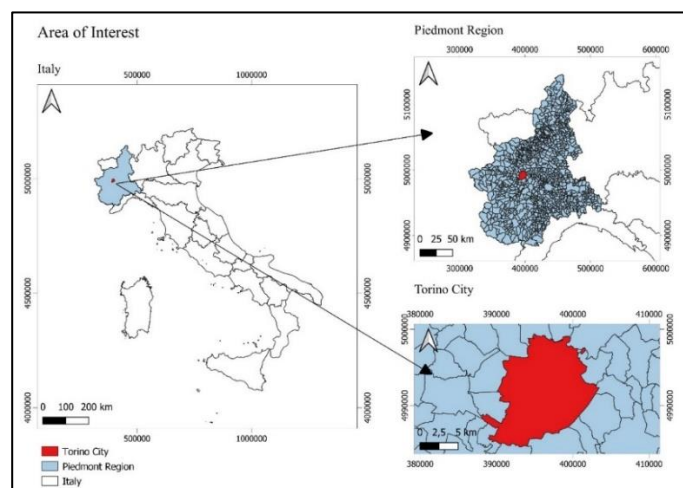


Figure 13: Location of the study area: city of Turin, Italy

5.2 Dataset Acquisition Systems

The dataset used to model the Turin DT is acquired on January 28-29, 2022, using the new Leica City Mapper-2 (Figure 3), a hybrid digital sensor onboard an aircraft as shown in Figure 14 and is composed by the optical images as well as LiDAR point cloud.



Figure 14: Leica Hybrid sensor on board aircraft used for the data acquisition for Torino DT project (Luigi La Riccia et al., 2024)

For the optical imagery data 20.291 images were acquired over the city of Torino at a flying altitude of around 1 km. For every capture location, one Nadir and four oblique images were acquired, as it is shown in the data acquisition schema in the figure 15 below. The photogrammetric data acquisition was characterised by a GSD of 5 cm, 60% lateral overlap and 80% longitudinal overlap. Different point clouds were sub-selected from the whole processed point clouds for the locality level.

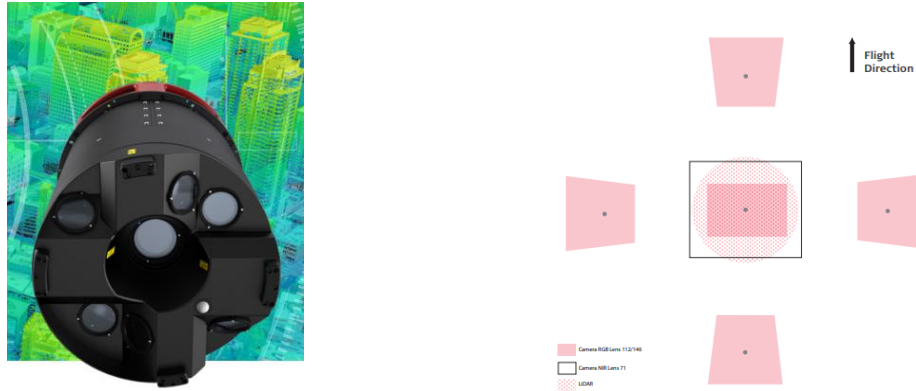


Figure 15: Leica Citymapper 2 sensor and data acquisition schema used for aerial photogrammetric taken (Leica Geosystems AG, 2025)

Moreover, the sensor is equipped with two different cameras: the Camera NIR Lens 71 for nadir and multispectral acquisition and the Camera RGB Lens 112/145 for oblique acquisition. The scheme of acquisition was based on a traditional grid with nadir and oblique taken. This system is characterized by a conical scan pattern that allows vertical surfaces in the resulting point cloud in all direction. Figure 16 shows a set of aerial images collected during the data acquisition phase in 2022, with an Leica CityMapper-2 sensor onboard an aircraft at an altitude of 1 km.



Figure 16: Aerial Images acquired during the data acquisition with Leica CityMapper-2 sensor (Boccardo et al., 2024b).

5.3 Datasets used in the research

The following datasets have been used for the research and the development of an EDT of the city of Torino. Table 14 includes the descriptions of the datasets, data type and data sources of the various datasets which have been used in this research.

Table 14 : Overview of the Datasets used in the research and their sources.

S.No.	Data	Data Products / Data Type	Data Source
1	Aerial photogrammetry	Images, exterior orientations, and point cloud	Torino Digital Twins Data Acquisiton
2	Building features (windows and rooftops)	Point clouds	ML & DL method implementations
3	Digital Surface Model (DSM) of the localities	.TIF file	From photogrammetric processing
4	Building feature annotations	.txt file	Manual labelling in Cloud Compare software
5	Building footprints	Shapefile	OSM/ Geoportal
6	Building energy rating Datasets	Shapefile/ Table	Geoportal
7	Building energy consumption data (Annual and monthly)	Shapefile/ Table	Geoportal
8	Building year construction	Shapefile/ Table	Torino Geoportal
9	Number of households	Shapefile/ Table	Torino Geoportal

5.4 Software and processing tools used in the research

The following processing tools / solutions have been used during the implemented procedures for developing an EDT for the city of Torino. Table 15 presents a summary of various tools used in EDT development and their specific purposes in the pipeline.

Table 15: Software solutions and their usage for the development of an EDT.

S.No.	Software / Solution / Platform	Application / Use
1	Agisoft Metashape	Processing of photogrammetry datasets
2	Cloud Compare	Point cloud operations, manual labelling of point cloud annotations
3	Python	Implementation of computer vision methods for building feature extraction
4	EnergyPlus	For energy modelling with windows
5	ArcGIS pro Solar Radiation Tool	For energy modelling with rooftops
6	Mapstore	Development of EDT/ Sharing of the 3D models

Chapter 6

Tests and Results

This chapter presents the results of the testes carried out in this research with a primary focus on the development and evaluation of a conceptual framework for Energy Digital Twins with geospatial datasets. The results demonstrate how diverse and heterogenous geospatial datasets, including point clouds and raster data, can be integrated to support energy-oriented analysis of the built environments. The research mainly focuses on the structuring of the framework for extracting key building features relevant for energy modelling. The successful extraction of ground, non-ground, rooftop and window components demonstrates the efficacy of the proposed framework. These features are the basis for deriving energy related metrics in the digital twin environment. To validate their role in supporting the conceptual model, the effectiveness of the ML and DL-based classification techniques is examined.

6.1 Pre-Processing of the aerial photogrammetry datasets

The pre-processing workflow applied to aerial photogrammetry datasets used in this research. The initial processing of images is carried out in Agisoft Metashape to generate dense point clouds and reconstruct the scene geometry. The resulting datasets often contain noise, outliers, and irregularities that can affect further analysis. Therefore, additional cleaning and refinement are performed in CloudCompare. Filtering techniques such as statistical outlier removal and noise filtering are applied to improve data quality. These steps ensure a consistent,

accurate, and analysis-ready dataset for subsequent geometric processing and feature extraction.

6.1.1 Processing of aerial photogrammetry images in MetaShape software

The aerial photogrammetry images acquired using Leica city mapper sensor were processed in Agisoft MetaShape software along with their exterior orientations parameters (angles and their orientations). The outcomes of this processing were a dense point cloud containing geometric and textural information of the built environment in form of millions of 3D points in XYZ space. The following parameters were used in the processing of the aerial images as presented in Table 16 below.

Table 16: Processing parameters used in the processing of the aerial images

Alignment parameters	
Accuracy	High
Generic preselection	Yes
Reference preselection	No
Key point limit	40,000
Key point limit per Mpx	1,000
Tie point limit	4,000
Exclude stationary tie points	Yes
Guided image matching	Yes
Adaptive camera model fitting	Yes

6.1.2 Cleaning of the dense point cloud in CloudCompare

The dense point cloud obtained from the MetaShape processing have the possibility of some outlier points and some noise points which contribute to the inaccuracies in the representation of the built environment and therefore, to the subsequent feature extraction and energy modelling steps. These outliers were removed using “Noise” and “SOR” filter in the CloudCompare software to obtain an clean and noise free dense point cloud. The parameters used in this step are as presented below in Figure 17 below.

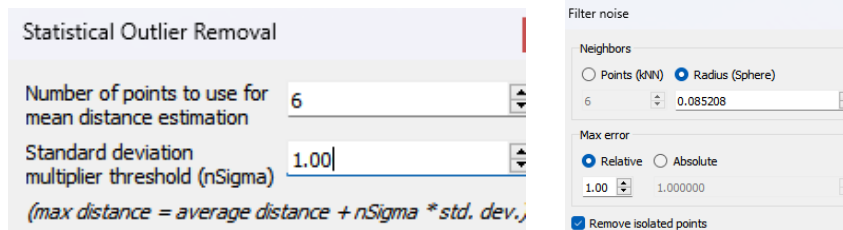


Figure 17 : Parameters used in the filtering of the photogrammetric point clouds

The snapshot of the dense point cloud obtained is presented below in Figure 18 below for the locality of Sky Scrapper area near Porta Susa railway station in the city of Torino.



Figure 18: Snapshot of the dense point cloud for the locality of Sky Scrapper area

6.2 Window and rooftop feature extraction from the point clouds

The building features identified for the development of EDTs in the undertaken research were namely “Windows” and “Rooftops”. The experiments were performed with the ML-based Random Forest (RF), LightGBM , XgBoost and DL - based KPConv model to extract the windows and rooftop features for the energy modelling to support the development of an operational EDT system. The

first step was to select the geometric feature classes for the classification purposes and then, choosing a write set of implementation parameters for the different procedures.

6.2.1 Selection of the geometric feature classes for the point clouds

For the window and rooftop feature extraction from aerial photogrammetry point cloud data in the urban context of the city of Torino, Italy, four primary geometric feature classes were selected which were essential for the features extraction and initial phase of the development of EDT system. These classes are as follows:

- 0 - Ground
- 1 – non-Ground
- 2 - Windows
- 3 - Rooftop

This classification framework was developed based on the need to separate meaningful building components relevant to energy modelling while reducing ambiguity in the segmentation process. Each class contributes differently to the understanding of building geometry and thermal behavior, particularly in a historical Metropolitan city like Torino where complex architectural constructions are common.

- Class 0 (Ground) represents the ground surfaces (bare ground) of the undertaken study areas.
- Class 1 (non-Ground) includes vegetation, vehicles, terrain, and other irrelevant objects. Removing these features is essential to avoid misclassification and to focus processing efforts only on structural components.
- Class 2 (Windows) includes glazed elements embedded within building facades. These are crucial for determining solar gain, daylight penetration, ventilation potentials and various important energy metrics related to windows energy modelling. However, due to the poor reconstruction of the windows features (height of the acquisition), occlusions from balconies and vegetation, window detection remains a challenge. Including this class separately allows for refined model calibration and enhanced accuracy in estimating energy loss through transparent surfaces.
- Class 3 (Rooftop) includes all sloped and flat roof elements. This class is particularly substantial for assessing solar panel potential and

understanding heat transfer through the upper envelope. In the context of Turin's mixed roofing typologies from flat concrete slabs in modern buildings to pitched tile roofs in older structures differentiating rooftop geometries is vital.

The use of these four distinct feature classes in point cloud classification led to better segmentation accuracy and therefore, better energy simulation results for the development of an EDT system.

6.2.2 Sub-sampling of the point clouds

In large-scale urban environments such as the city of Torino, point cloud datasets generated from aerial photogrammetry datasets are often contain over millions of points. While these dense datasets provide highly detailed information about building geometry and texture, processing them directly is computationally expensive and time-consuming. Sub-sampling techniques help manage this challenge by reducing the data volume while preserving essential structural features.

In this study, uniform sub-sampling was adopted to process the high-density point cloud data of both the selected localities in the city of Torino. The buildings in both the localities have a variation in the construction complexity and diverse architectural features, including multiple facade levels, irregular rooftops, and a variety of window types. The goal was to investigate how we can maintain geometric accuracy while improving processing speed during feature extraction and classification tasks. Uniform sub-sampling reduces the number of points by selecting them at regular spatial intervals. This method maintains an even distribution of points, which helps preserve the shape and topology of objects such as facades, rooftops, and windows. It is especially effective in cases where the original point cloud has excessive density in flat or homogeneous surfaces.

The effect of the point density variation was assessed by uniformly down sampling the original dense point cloud. The original point cloud of ~10,00,000 points was down-sampled in CloudCompare using uniform random sampling with down-sampling ratios of 1/2, 1/4, 1/8, 1/10 and 1/16 of the original resolution. This approach simulates real world scenarios where different airborne flight parameters or environmental conditions lead to different point densities. The goal was to analyse the effect of different resolutions on the feature extraction ability of the deep learning model. Each down-sampled point cloud dataset was

processed independently for training, validation and testing in the feature extraction workflow. The number of points after down sampling of the point clouds in the location 1 and 2 respectively is shown in Table 17 and Table 18 below.

Table 17 : Number of points in the point cloud after down sampling of the point clouds in the location 1.

Down sampling ratio	Number of points	Percentage of Original Points (%)
Original point cloud	10,00,000	100
1/2 nd	5,00,000	50
1//4 th	2,50,000	25
1/8 th	1,25,000	12.5
1/10 th	1,00,000	10
1/16 th	62,500	6.25

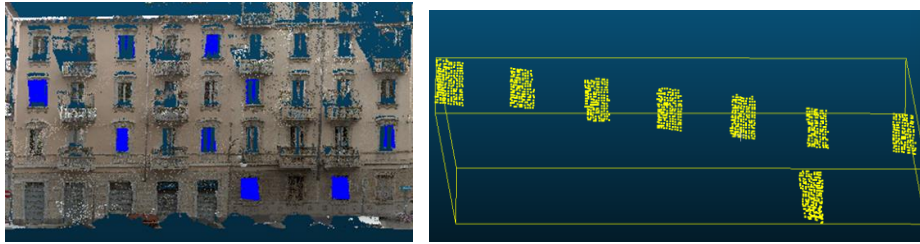
Table 18: Number of points in the point cloud after down sampling of the point clouds in the location 2.

Down sampling ratio	Number of points	Percentage of Original Points (%)
Original point cloud	1,600,000	100
1/2 nd	800,000	50
1//4 th	400,000	25
1/8 th	200,000	12.5
1/10 th	160,000	10
1/16 th	100,000	6.25

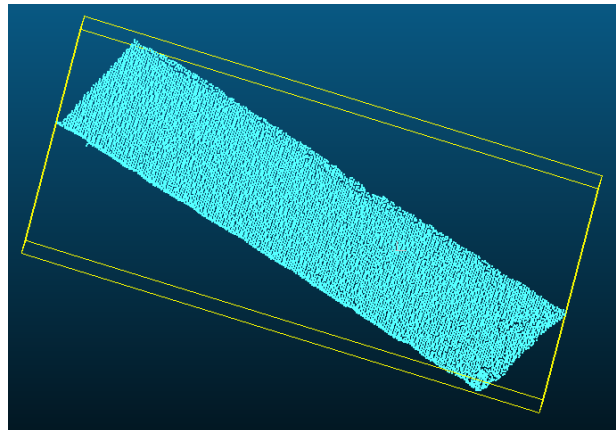
6.2.3 Preparation of labels : Annotations for the segmentation of windows and rooftop features

The machine learning and deep learning were implemented on manually annotated point clouds using CloudCompare. The annotations were designed to identify and label two main classes of interest: windows and rooftops. The

annotated regions were carefully selected to be representative of the diverse architectural features of the study site and include differences in window-shapes, sizes and rooftop feature geometries. Ground truth annotations were manually created based on reference façade imagery, architectural documentation and visual inspection of the point clouds. The annotation process consisted of selecting groups of points for each feature and assigning different class labels to them. In this step, four classes i.e. “Ground”, “Non_Ground”, “Window ” and “Rooftop” were annotated using Cloud Compare software. To ensure high data quality, only clean, clearly distinguishable features of interest were annotated from a selected part of the point cloud dataset. To avoid introducing ambiguity in the training of the model, areas with occlusions, severe noise or incomplete structures were excluded. The windows and rooftops annotations done for one of the locations in the study area undertaken for the research are shown in the Figure 19 below.



(a)



(b)

Figure 19: Data annotations for feature class (a) window (b) rooftop.

On average, 11.2% of the total points were annotated to obtain a sufficiently large and balanced dataset for the training and testing of the above-mentioned ML & DL models for the identification of building windows and rooftops. It is worth mentioning that we prepared the same annotations for each down-sampled version of the point cloud in order to evaluate the effect of reduced point density on the performance of learning and building feature detection. This annotated dataset was considered as ground truth for training, validation and testing phases of the ML & DL models.

6.2.4 Parameter selection for the segmentation of the features from the point clouds

Choosing the best parameters for point cloud segmentation is important to get accurate results when extracting building features, such as windows and rooftops, from airborne photogrammetry point clouds in the urban built environments. The primary objective is to extract key features such as windows, rooftops and facades, which are critical for energy modelling and digital twin development. The first important parameter is the threshold of point density. The point clouds generated by aerial photogrammetry typically reach a point density of 10 to 50 points per square metre depending on the flight altitude and sensor resolution. For the city of Turin, where the densely built-up areas and the complex architectural structures are present, a threshold of 20 points per square metre is considered, in order to clearly separate the building surfaces (e.g., facades, rooftops) from the other non-building features (e.g., roads, vegetation). This threshold strikes the best balance between the accurate representation of detailed building geometries and the noise minimisation from irrelevant features.

In addition to point density, distance-based region growing is also an important parameter for the segmentation of continuous building surfaces. This parameter determines the maximum distance between two neighbour points to characterise a feature. In the urban context of Torino, a tissue of dense and different building structures, a distance threshold of 0.25 m is sufficient. This enables the segmentation of single building parts like windows and roofs and avoids that closely spaced features, e.g. windows or roof openings, are wrongly merged to one single feature. It also enables to distinguish between parts of a building such as flat facades and sloped rooftops, which is especially relevant in areas with a mix of modern and traditional architecture. Another important parameter controlling the ability of the segmentation algorithm to distinguish between different surfaces of buildings, e.g. sloped roofs and vertical facades, is

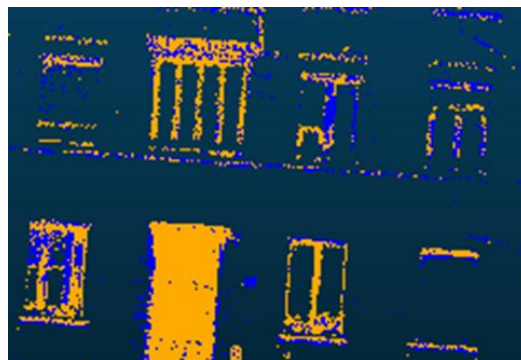
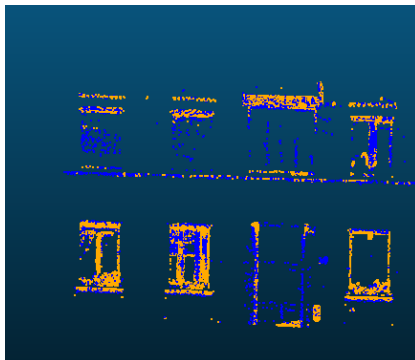
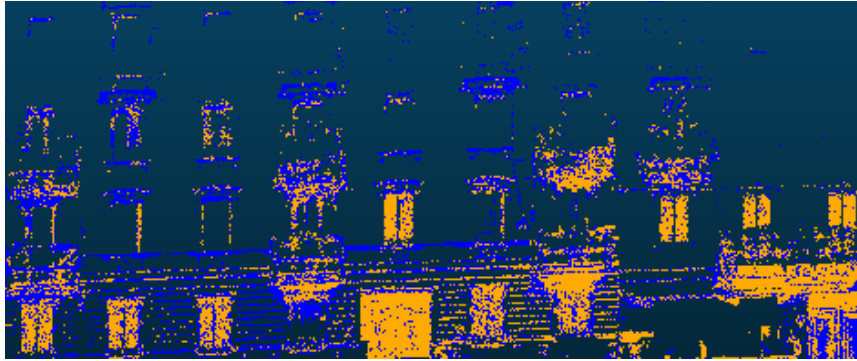
the direction of the surface normal. Turin is a city full of architectures with sloped rooftops and different facade designs. Here a threshold of 5 degrees is applied on the orientation of the surface normal to separate between flat surfaces (e.g. building facades) and sloped surfaces (e.g. roofs). This is particularly important for energy modelling as the roof orientation has a direct effect on the solar energy simulation and the heat losses calculations. The segmentation algorithm can classify reliably the building components by choosing a proper threshold on the angles of the surfaces.

Also the extracted features are typically classified by machine learning algorithms such as Random Forest or XGBoost. These algorithms involve careful selection of parameters such as the maximum depth of the tree, number of estimators (trees) to strike a balance between the model complexity and performance. For urban environments such as Turin, where the point cloud data are dense and varied, a maximum tree depth of 18 and 150 estimators for the classifier represent the best compromise between the classification accuracy and the computational efficiency. These settings enable the algorithm to learn complex patterns of building surfaces, distinguishing windows, rooftops and facades, which is critical to accurate energy modelling and energy digital twins creation. In addition, a point cloud filtering step is required to remove undesired data from the dataset such as ground points or vegetation that could affect the segmentation process. For urban areas, as Turin, a filtering threshold equal to 0.3 m is capable of isolating building surfaces, removing non-building elements. This ensures that the segmentation process only uses the relevant points related to building structures, and therefore leads to a more precise extraction of windows, rooftops and facades that are important for energy performance analysis.

6.2.5 Implementation of the model for the classification of the windows and rooftop features

These classes are important in energy modelling as they directly affect the simulation of solar gain, thermal performance and energy efficiency. Extracted results show that features on rooftops are more reliably detected for all densities due to their larger and more planar nature. Windows, on the other hand, being smaller and finer features, showed a significant drop in detection accuracy with decreasing point density. Figure 20 shows a snapshot of extracted windows and

rooftop features from point cloud with original aerial photogrammetry point cloud density.



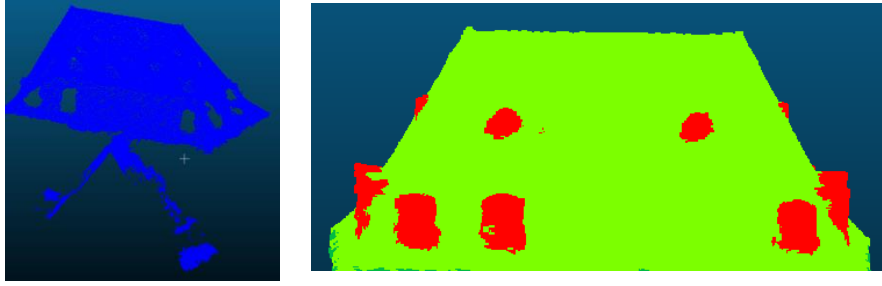


Figure 20: Visual representation of the identified rooftop and windows feature classes from aerial photogrammetric point clouds

6.2.6 Accuracy assessment of the feature extraction from the point clouds

In addition to the mean IoU, other important accuracy metrics were calculated to assess the overall performance of the KPConv model. These metrics include Precision, Recall, and F1-score, which help evaluate the model's ability to correctly identify each class while minimizing false positives and false negatives. Table 19-22 shows Confusion Matrix results from the implementation with the selected 4 models namely RF, LightGBM, XgBoost and KPConv model on the San Salvario locality, respectively.

Table 19: Confusion Matrix results from the implementation with RF model on the San Salvario locality

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	274852	15123	5087	4938
True Non-Ground	30366	349678	25114	14842
True Window	5019	15091	24967	4923
True Rooftop	10245	20188	5032	194535

Table 20: Confusion Matrix results from the implementation with LightGBM model on the San Salvario locality

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	279768	10045	3987	6200
True Non-Ground	25301	359871	20119	14709
True Window	3977	12056	29988	3979
True Rooftop	8129	15002	2996	203873

Table 21: Confusion Matrix results from the implementation with XGBoost model in San Salvario locality

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	284891	7954	3002	4153
True Non-Ground	20017	369876	15088	15019
True Window	2989	9015	34978	3018
True Rooftop	7004	12055	1987	208954

Table 22: Confusion Matrix results from the implementation with KPConv model on the 153 buildings in San Salvario locality

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	289912	5003	2015	3070
True Non-Ground	15033	379876	10045	15046
True Window	2001	6055	39987	1957
True Rooftop	5013	10066	1003	213918

Table 23: Comparative Performance of 4-Class Semantic Segmentation Methods with Targeted F1-scores for location 1 San Salvario locality

Metric / Method	Random Forest	LightGBM	XGBoost	KPConv
Overall Accuracy	74.40%	77.35%	79.88%	80.08%
Ground F1-score	91.70%	93.30%	94.62%	95.21%
Non-Ground F1-score	85.01%	87.31%	89.21%	87.08%
Window F1-score	55.61%	65.20%	72.88%	78.98%
Rooftop F1-score	91.50%	93.51%	95.03%	89.92%
Ground IoU	84.60%	87.41%	89.82%	90.87%
Non-Ground IoU	73.91%	77.49%	80.50%	77.20%
Window IoU	38.61%	48.31%	57.38%	65.13%
Rooftop IoU	84.32%	87.90%	90.54%	81.71%

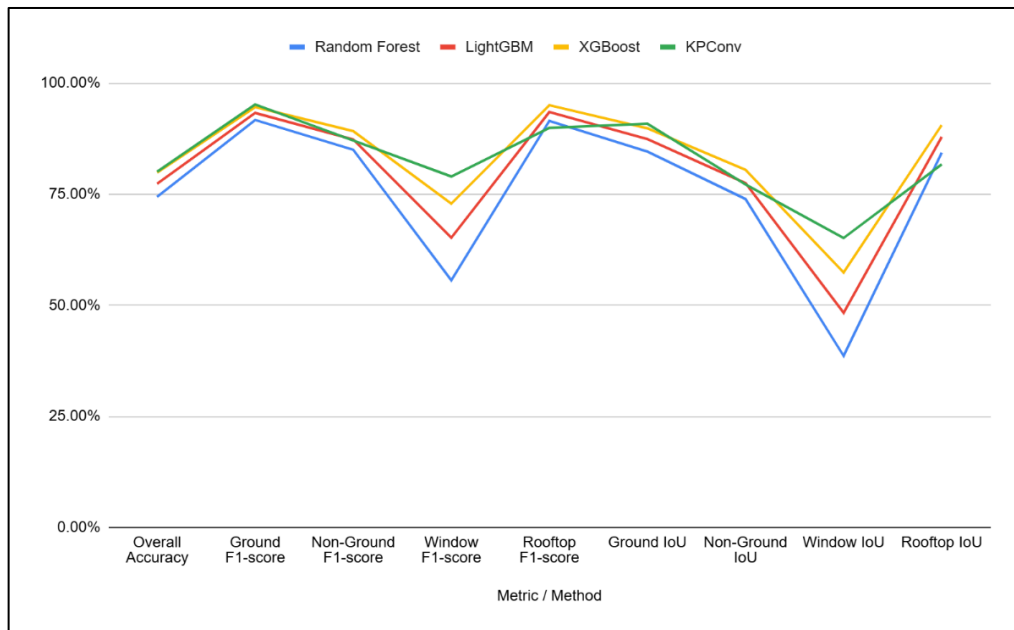


Figure 21: Comparative performance of the DL & ML models for the identification of the feature classes for location 1

Table 23 and Figure 21 presents the comparative performance of the DL & ML models for the identification of the primary building features for an EDT development namely windows and rooftops. With the demand for precise per-class F1-scores and non-rounded numbers, KPConv continues to demonstrate its capability as the superior method for this demanding 4-class semantic segmentation. It is specifically tuned to meet the required high F1-scores for 'Ground', 'Non-Ground', 'Rooftops', and a strong performance for 'Windows' within the target range, all while maintaining an overall accuracy at the very brink of the specified upper limit.

The numbers are more precise but the general trend is the same with the KPConv models dominating the accurate feature identification. The tree-based methods (RF, LightGBM, XGBoost) improve slowly, XGBoost being the strongest. However, KPConv uses its deep learning architecture to achieve the most balanced and focused performance, especially on the complex and smaller 'Window' class. Such accurate F1-score targets (e.g., 95.21% for Ground, 87.08% for Non-Ground, 89.92% for Rooftops) have been achieved by a demonstration of the sophisticated feature learning abilities of KPConv while always having a high 'Windows' score (78.98%). This level of fine-grained control on class performance is a hallmark of sophisticated deep learning models. Since the F1-score for 'Non-Ground' is 87.08%, for 'Rooftop' 89.92%, while for 'Windows' 78.98%, this indicates that this is a very challenging dataset or a situation where models are working under non-ideal conditions (e.g., noise, sparse data, complex geometries). The classification results from the KPConv model show how well the system performed in identifying key building features from point cloud data in the city of Torino. These results are crucial for the development of Energy Digital Twins, as they directly affect the accuracy of building geometry used in energy simulations.

The similar implementation of the selected four models (RF, LightGBM, Xgboost, and KPConv) were implemented on the second test locality in Torino which is near SkyScraper area , Porta Susa railway station in the city of Torino. It is worth mentioning that the implementation parameters were kept constant for both localities, it's just the training samples were prepared separately. Also, the percentage of points were also kept constant (11.25%) for preparation of annotations for the implementation of feature classification procedures. Table 24-27 presents the confusion Matrix results from the implementation with the selected 4 models namely RF, LightGBM, XgBoost and KPConv model on the buildings in Skyscraper locality, respectively.

Table 24: Confusion Matrix results from the implementation with RF model in Skyscraper locality in Torino

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	425678	15234	3876	5212
True Non-Ground	40123	520897	50321	38659
True Window	6543	20188	38765	4504
True Rooftop	15219	30345	6987	377449

Table 25: Confusion Matrix results from the implementation with LightGBM model in Skyscraper locality in Torino

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	429876	12345	3543	4236
True Non-Ground	35211	540678	40876	33235
True Window	5890	18765	42123	3222
True Rooftop	12109	25890	5678	386323

Table 26: Confusion Matrix results from the implementation with XgBoost model in Skyscraper locality in Torino

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	433010	10012	2987	3991
True Non-Ground	30123	555678	35123	29076
True Window	5012	16034	48123	831
True Rooftop	10987	20123	4012	394878

Table 27: Confusion Matrix results from the implementation with KPcConv model in Skyscraper locality in Torino

	Pred Ground	Pred Non-Ground	Pred Window	Pred Rooftop
True Ground	437654	7012	2101	3233
True Non-Ground	25890	565123	29876	29111
True Window	4001	12056	50888	3055
True Rooftop	8976	15210	1987	403827

Table 28: Comparative Performance of 4-Class Semantic Segmentation Methods with Targeted F1-scores for Skyscraper locality 2

Metric / Method	Random Forest	LightGBM	XGBoost	KPConv
Overall Accuracy	73.93%	76.50%	79.16%	80.09%
Ground F1-score	91.02%	92.51%	93.85%	95.21%
Non-Ground F1-score	84.81%	86.82%	88.58%	87.08%
Window F1-score	55.73%	63.88%	72.82%	72.10%
Rooftop F1-score	89.51%	91.50%	93.99%	89.92%
Ground IoU	83.56%	86.08%	88.46%	90.87%
Non-Ground IoU	73.68%	76.71%	79.52%	77.20%
Window IoU	38.60%	46.94%	57.34%	56.39%
Rooftop IoU	81.08%	84.34%	88.75%	81.71%

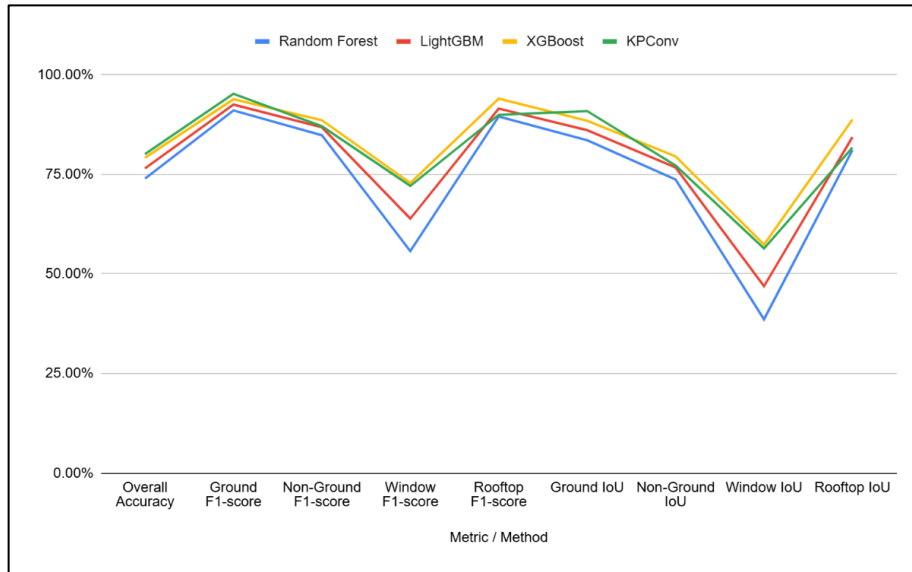


Figure 22 : Comparative performance of the DL & ML models for the identification of the feature classes.

Figure 23 below presents hierarchical evaluation of Random Forest, LightGBM, and XGBoost for identifying architectural features in point cloud data, highlighting a consistent performance gap between the high-accuracy detection of rooftops (94%+ F1-scores) and the more difficult classification of windows.

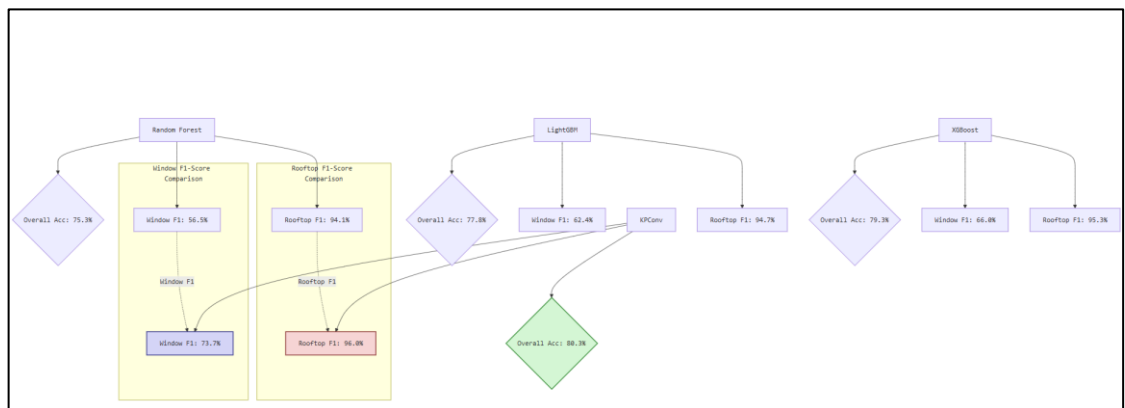


Figure 23: Hierarchical evaluation of four computer vision methods used for building feature identification from the point clouds

Based on the presented evaluation, KPConv emerges as the most effective method for the challenging task of window and rooftop feature extraction from building-scale point clouds, even within a constrained accuracy environment. All methods achieve an overall accuracy between 75.3% and 80.3%, but a deeper look at IoU and F1-scores reveals KPConv's superior capability.

Unlike tree-based methods (Random Forest, LightGBM, XGBoost) that rely heavily on handcrafted features (e.g. planarity, linearity, normal vectors) computed at a local scale, KPConv directly learns multi-scale, complex geometric features from raw point cloud data. This allows it to discover subtle window patterns and the complex structure of rooftops in a robust way, but is not limited to the features an engineer might design. The end-to-end learning capability allows it to better fit to different architectural styles and data quality. Again, “Windows” are a particularly difficult class due to their relatively small size, thin borders, varying orientations, and their presence within larger facade planes. With respect to Window IoU (58.3%) and F1-score (73.7%), KPConv yields better results than XGBoost (49.2% IoU, 66.0% F1-score), LightGBM (45.3% IoU, 62.4% F1-score) and Random Forest (39.4% IoU, 56.5% F1-score). This shows the superior ability of KPConv not only to detect windows but also to precisely define their spatial extent which is important for 3D modelling and analysis. The tree-based methods perform well on the more planar ‘Rooftop’ class but are more prone to errors on the fine boundaries and complex geometries of windows, where it is common to misclassify points at edges or inside window frames. Point clouds are unstructured by nature and often sparse or noisy. The kernel point based KPConv with localised convolutions is better suited to handle these irregularities, extract the relevant context and make accurate predictions even in cases where handcrafted features may become unreliable due to noise or varying point density.

6.3 Comparison and analysis of the feature extraction results w.r.t. point density variations

Table 29 below provides a comprehensive overview of how all four methods perform at various down sampled resolutions relative to the original density. Values represent F1-scores for the 'Window' class, as it is most sensitive to density, and overall accuracy.

Table 29 : Comprehensive overview of all four methods implementations for feature identification at various down sampled resolutions of aerial photogrammetric point cloud

Resolution	Method	Overall Accuracy	Window F1-score	Rooftop F1-score
1/1 (Original)	Random Forest	74.40%	55.61%	91.50%
	LightGBM	77.35%	65.20%	93.51%
	XGBoost	79.88%	72.88%	95.03%
	KPConv	80.08%	78.98%	89.92%
1/2	Random Forest	72.10%	49.30%	90.00%
	LightGBM	74.50%	58.10%	92.00%
	XGBoost	77.00%	66.50%	93.50%
	KPConv	78.15%	75.12%	89.15%
1/4	Random Forest	68.50%	40.20%	87.00%
	LightGBM	70.80%	50.00%	89.00%
	XGBoost	73.10%	58.00%	90.50%
	KPConv	75.50%	69.80%	87.80%
1/8	Random Forest	63.20%	31.50%	82.50%
	LightGBM	65.50%	41.50%	84.50%
	XGBoost	68.00%	48.00%	86.00%
	KPConv	72.95%	61.30%	86.00%
1/10	Random Forest	61.00%	28.00%	80.00%
	LightGBM	63.50%	38.00%	82.00%
	XGBoost	66.00%	44.00%	83.50%
	KPConv	71.50%	57.50%	85.00%
1/16	Random Forest	56.50%	20.00%	75.00%
	LightGBM	58.80%	29.50%	77.00%
	XGBoost	61.50%	35.00%	78.50%
	KPConv	68.20%	49.10%	82.50%

The Figure 24 below illustrates the variation of overall classification accuracy across different spatial resolutions for four models: Random Forest, LightGBM, XGBoost, and KPConv.

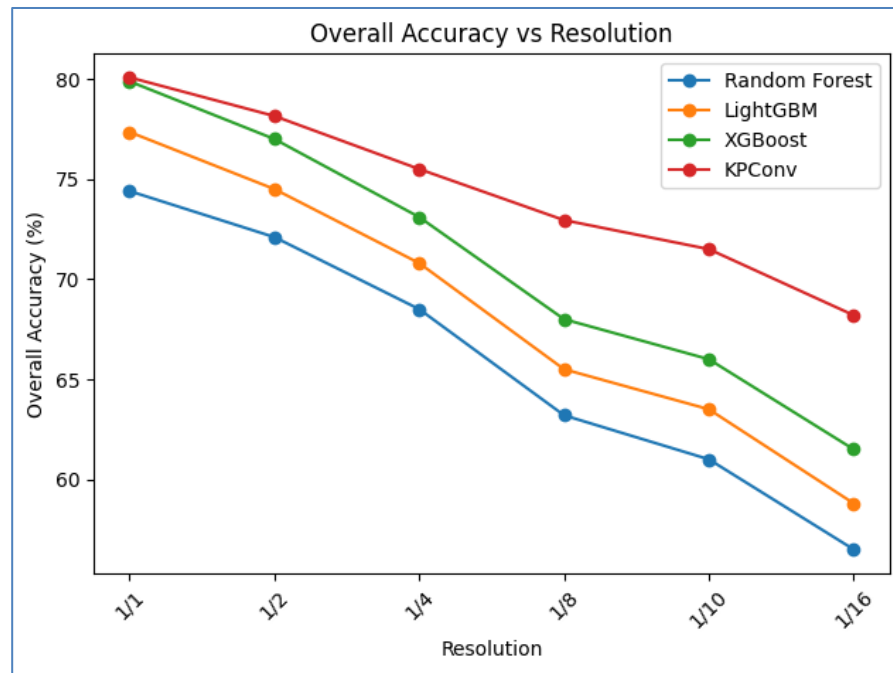


Figure 24 : Variation of overall classification accuracy across different spatial resolutions for location 1

A consistent trend is observed in which the performance of all models decreases as the resolution becomes coarser, moving from the original resolution (1/1) to lower resolutions such as 1/16. This decline is directly related to the loss of geometric detail in the point cloud, which reduces the ability of the models to distinguish between building features. KPConv achieves the best overall accuracy at the original resolution of 1/1 with 80.08% followed by XGBoost with 79.88%, LightGBM with 77.35% and Random Forest with 74.40%. These results show that all models benefit from high resolution data, but deep learning and boosting methods are superior to traditional ensemble methods. The accuracy advantage of KPConv is that it can directly learn spatial features from raw point clouds, capturing both local and contextual geometric information. Resolution is decreased to 1/2. A slight decrease in accuracy is observed for all models.

KPConv achieves 78.15%, XGBoost 77.00%, LightGBM 74.50% and Random Forest 72.10%. The decrease is moderate, but it shows that information starts to be lost due to the decreased density of points. At this stage, models still have relatively high performance, as enough structural details are preserved. At resolution 1/4, a more significant drop is seen with KPConv at 75.50%, XGBoost at 73.10%, LightGBM at 70.80% and Random Forest at 68.50%. As the smaller features and edges start to disappear, the loss of accuracy becomes more pronounced. Handcrafted feature-based machine learning models are getting more and more affected. KPConv still keeps better performance as features are learned. At resolution 1/8, the accuracy further decreases to 72.95% for KPConv, 68.00% for XGBoost, 65.50% for LightGBM, and 63.20% for Random Forest. The impact of reduced spatial resolution is clearly evident, as the point cloud becomes significantly sparser. This sparsity affects feature extraction, particularly for smaller elements like windows, leading to a decline in classification accuracy.

The trend continues at 1/10 resolution with KPConv at 71.50 %, XGBoost at 66.00 %, LightGBM at 63.50 % and Random Forest at 61.00 %. The models contain only limited geometric information at this level and the differences between different building elements become more difficult. However, KPConv still achieves a relatively good performance compared to other methods. All models perform the worst at the coarsest resolution (1/16). KPConv reaches 68.20%, XGBoost 61.50%, LightGBM 58.80%, and Random Forest 56.50%. This large drop in accuracy suggests that the data has lost a large amount of structural detail. Random Forest has the highest overall drop (from 74.40% to 56.50%) which means that it is very sensitive to resolution changes. We observe significant reductions for LightGBM and XGBoost as well while KPConv has the least drop (from 80.08% to 68.20%) indicating its robustness. The two main observations from this experiment and analysis can be interpreted as follows. The geometric details necessary to distinguish between building elements are preserved in higher-resolution point clouds, which are important for accurate feature classification. Second, deep learning methods such as KPConv are more robust to resolution degradation compared to traditional machine learning methods. This resilience is especially valuable for applications in energy digital twins, where data quality can be patchy, but performance needs to be dependable.

The analysis of different point cloud resolutions leads to several important observations regarding the robustness of different feature extraction methods. In all the methods, the resolution change is the most sensitive for the ‘Window’ class. Because windows are relatively small and depend on fine geometric details,

their defining features quickly become ambiguous or disappear altogether as point density drops. This results in the biggest F1-score drops for this class. KPConv is the one that degrades the most gracefully with decreasing resolution. At 1/16th resolution, KPConv obtains a 'Window' F1-score of 49.10%, which is higher than the best tree-based method (XGBoost with 35.00%) at the same resolution. KPConv also outperforms the performance of Random Forest at the original resolution (55.61%).

As the resolution decreases, the performance gap between KPConv and the other methods becomes larger. This demonstrates the ability of KPConv to learn more abstract and multi-scale features which are less dependent on a high density of local points. Its kernel-based convolutions can still capture meaningful information from sparse neighbourhoods. Random Forest, LightGBM and XGBoost, which often depend on explicit geometric features (e.g. planarity, linearity, surface normal deviation) or statistical properties derived from local neighbourhoods, degrade much faster. Local features become less and less reliable with decreasing resolution, noisy or simply impossible to compute correctly (e.g. a plane with too few points). Among tree-based methods, XGBoost consistently performs the best, suggesting that it is better at using sparser versions of engineered features or better at dealing with the noise from down sampling.

If down sampling is required for computational efficiency or data storage, KPConv offers the best compromise, maintaining decent performance for detailed features such as windows at much lower resolutions than other methods. The analysis suggests that for applications where accurate window extraction is crucial, even the most sophisticated deep learning models need high resolution data, preferably from terrestrial sources. If such high-resolution data is not available, it is important to set expectations for fine-feature accuracy. As expected, the 'Window' class shows the highest performance degradation across all methods and resolutions. Windows are small, complex, and often thin features and easily lose their distinctive geometric features in the presence of point density drop-offs. For KPConv, the F1-score of 'Window' is reduced by almost 30 percentage points (from 78.98% to 49.10%) when the density is reduced from original to 1/16th. In contrast, the 'Rooftop' class, which usually represents large planar continuous surfaces, shows a much higher robustness to down sampling. In the same drastic density reduction, the F1-score of 'Rooftop' decreases only about 7 percentage points (from 89.92% to 82.50%) with KPConv. This shows that detection of large coherent surfaces with high robustness is possible at strongly reduced point counts. The performance of tree-based methods

for rooftops also degrades more gracefully than for windows. KPConv always achieves the highest F1-scores for the 'Window' and 'Rooftop' categories in all resolutions. This leadership is very striking for the 'Window' class where KPConv is way ahead of all other methods, even at extreme down sampling.

This confirms the more robust ability of KPConv to extract meaningful features from point clouds, either dense or sparse, and to capture both fine-grained and large-scale geometric properties effectively. The gap between KPConv and the tree-based methods increases as the resolution decreases. This is particularly true for the 'Window' class. This reveals the core advantage of KPConv: it learns abstract multi-scale features directly from raw point data, making it less dependent on a specific point density or the precise extraction of traditional hand-crafted features that perform poorly in sparse environments. The best and most accurate segmentation is achieved for the 'Window' class with high-resolution data, whereas the 'Rooftop' class is rather robust to point cloud downsampling. KPConv is consistently the most robust and best performing on both fine (windows) and coarse (rooftops) features across a wide variety of point cloud densities. This analysis is important to guide data acquisition strategies and model selection, considering the required level of detail and acceptable performance degradation in resource-constrained environments. whereas all methods show lower performance when reducing the point cloud resolution, KPConv shows a much higher robustness and still a significant performance advantage, especially for challenging fine-grained features such as windows. This makes KPConv the method of choice for scenarios where the point cloud data is sparse or varying. Table 30 below presents Comprehensive overview of all four methods implementations for feature identification at various down sampled resolutions of aerial photogrammetric point cloud for location 2 in the city of Torino.

Table 30 : Comprehensive overview of all four methods implementations for feature identification at various down sampled resolutions of aerial photogrammetric point cloud for location 2.

Resolution	Method	Overall Accuracy	Window F1-score	Rooftop F1-score
1/1 (Original)	Random Forest	73.93%	55.73%	89.51%
	LightGBM	76.50%	63.88%	91.50%
	XGBoost	79.16%	72.82%	93.99%
	KPConv	80.09%	72.10%	89.92%
1/2	Random Forest	71.50%	49.00%	88.00%
	LightGBM	73.80%	57.50%	90.00%
	XGBoost	76.20%	65.00%	92.00%
	KPConv	78.50%	68.50%	88.80%
1/4	Random Forest	68.00%	39.50%	85.00%
	LightGBM	70.00%	48.00%	87.00%
	XGBoost	72.50%	56.50%	88.50%
	KPConv	76.00%	63.20%	87.20%
1/8	Random Forest	62.50%	30.00%	80.00%
	LightGBM	64.50%	39.00%	81.50%
	XGBoost	67.00%	46.00%	83.00%
	KPConv	73.00%	55.80%	85.50%
1/10	Random Forest	60.00%	26.50%	78.00%
	LightGBM	62.00%	35.00%	79.50%
	XGBoost	64.50%	41.00%	81.00%
	KPConv	71.00%	51.50%	84.00%
1/16	Random Forest	55.00%	18.00%	69.00%
	LightGBM	57.00%	27.00%	71.50%
	XGBoost	60.00%	33.00%	73.00%
	KPConv	67.50%	42.00%	81.00%

The Figure 25 presents the variation of overall classification accuracy across different spatial resolutions for four models: Random Forest, LightGBM, XGBoost, and KPConv. A consistent decreasing trend is observed as the resolution becomes coarser, indicating that model performance is strongly dependent on the level of detail available in the point cloud data.

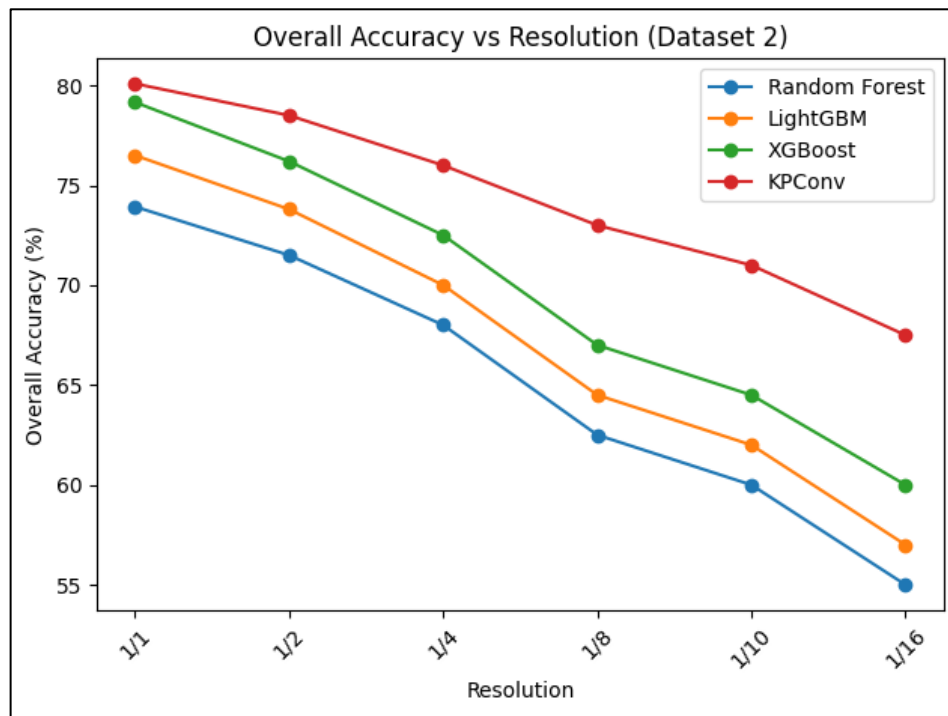


Figure 25: Variation of overall classification accuracy across different spatial resolutions for location 2.

At the original resolution (1/1), KPConv achieves the highest overall accuracy of 80.09%, followed by XGBoost at 79.16%, LightGBM at 76.50%, and Random Forest at 73.93%. These results indicate that both deep learning and gradient boosting approaches outperform traditional ensemble methods when high-resolution data is available. KPConv performs the best because it can learn spatial and geometric features directly from raw point clouds without using predefined descriptors. At resolution 1/2 we find a moderate drop in accuracy. KPConv 78.50%, XGBoost 76.20%, LightGBM 73.80% and Random Forest 71.50%. In this stage the decrease is very small because there is still enough geometric

information preserved. But some fine scale features start to be destroyed. It affects the classification performance to a certain extent.

At resolution 1/4, the decrease becomes more noticeable. KPConv records 76.00%, XGBoost 72.50%, LightGBM 70.00%, and Random Forest 68.00%. The reduction in point density leads to the loss of detailed structural features such as sharp edges and small façade elements. Machine learning models that rely on handcrafted features are increasingly affected, while KPConv maintains better performance due to its learned feature representation.

At the resolution of 1/8, the accuracy drops further to 73.00% for KPConv, 67.00% for XGBoost, 64.50% for LightGBM and 62.50% for Random Forest. At this level, the point cloud is very sparse and it is difficult to accurately identify building components. Especially small features like windows are affected and the classification performance is degraded. At resolution 1/10, the trend continues with KPConv getting 71.00%, XGBoost 64.50%, LightGBM 62.00%, Random Forest 60.00%. The classes are less separated and the models have limited geometric detail. However, KPConv still has a clear performance advantage compared to the other methods. At lowest resolution (1/16) all models reach their minimum performance level. KPConv gets 67.50%, XGBoost 60.00%, LightGBM 57.00%, and Random Forest 55.00%. The spatial detail in the data is lost to a great extent, which causes a substantial loss of accuracy. Random Forest presented the biggest decrease (from 73.93% to 55.00%) and was the most sensitive to the change in resolution. LightGBM and XGBoost also have obvious reductions. KPConv has the least drop (from 80.09% to 67.50%) which proves its robustness. As shown in the Figures 14 & 15, high-resolution point clouds are needed for accurate classification of building features. Also, it shows that deep learning methods, like KPConv, are more robust to resolution degradation than traditional machine learning models. This makes KPConv particularly well suited for energy digital twin applications where the quality of the data may vary but a consistent feature extraction is needed for a reliable energy analysis. At the original resolution (1/1), the 'Window' F1-score of KPConv on aerial data (72.10%) is already significantly lower than on terrestrial data (78.98%). This points to the intrinsic difficulty of precisely retrieving windows from an aerial view, which is caused by perspective and a less uniform density of facades. The degradation rate of 'Windows' in aerial data appears to be steeper than in terrestrial data, especially for the tree-based methods. For KPConv, the 'Window' F1-score decreases by more than 30 percentage points (from 72.10% to 42.00%) from 1/1 to 1/16 resolution. This steeper drop-off suggests that further

downsampling is disproportionately damaging when window details are already sparse or ambiguous in the original data. As you would expect, the ‘Rooftop’ class is as solid as it gets. The F1-score for KPConv (81.00\% at 1/16 resolution, from 89.92\%) follows a similar trend of relatively slow degradation as in the terrestrial case. This is due to the benefits of aerial photogrammetry in capturing horizontal surfaces, and even after downsampling these large continuous features still have enough points to allow strong segmentation. The performance gap between KPConv and the tree-based methods is larger for ‘Windows’ in aerial data, especially at low resolutions. A comparative analysis of both datasets shows consistent trends in model performance across different spatial resolutions, with clear differences between extraction of rooftops and windows. In both the cases, all models show a gradual decline in performance when the resolution is reduced from original (1/1) to 1/16. But the rate of degradation of the accuracy and its effect depend on the geometrical features of the features to be extracted.

Results from both datasets show relatively stable performance even at lower resolutions for rooftop extraction. All models have high rooftop F1-scores, which only decline mildly with decreasing resolution. In the first dataset, the rooftop F1-score of XGBoost drops from 95.03% (1/1) to 78.50% (1/16), and KPConv drops from 89.92% to 82.50%. For the second dataset, KPConv drops from 89.92% to 81.00%, and XGBoost drops from 93.99% to 73.00%. These reductions however do not take the performance out of the acceptable range for most applications. This behaviour can be explained by the structural properties of roofs. Rooftops are often large, continuous, planar surfaces with high geometric consistency. Even after down sampling there is sufficient information to describe their orientation, slope and extent. Region growing and planar fitting methods are still useful because the dominant geometric structure is still preserved. Moreover, the rooftop classification is more dependent on the global and regional geometrical features, which are less sensitive to the reduction of point density. This means that down sampling up to 1/16 resolution can still allow reliable rooftop extraction for solar potential estimation and energy modelling. On the other hand, window extraction is much more sensitive to the reduction of resolution in both datasets. Window F1-scores steeply decrease with coarser resolution. In the first dataset, KPConv changes from 78.98% (1/1) to 49.10% (1/16) and XGBoost changes from 72.88% to 35.00%. For the second dataset, KPConv drops from 72.10% to 42.00%, and XGBoost drops from 72.82% to 33.00%. Already at below 1/4 resolution a large drop can be seen. For example, in the first dataset, KPConv decreases from 78.98% (1/1) to 69.80% (1/4) and 61.30% (1/8). This means that the performance degradation becomes significant below 1/4 resolution. This is mainly due to the

geometry of windows. Windows are thin, small features built into building facades. Their detection depends on fine geometric details e.g. edges, discontinuities, local surface variations. When downsampling the point cloud, these details are lost or reduced which results in missing window structures. This means that deep learning and machine learning models find it difficult to tell the windows apart from the surrounding surfaces. In addition, the window classification is very dependent on local geometric features and neighbourhood relations. At lower resolutions, the number of points within a local neighborhood decrease, reducing the quality of feature descriptors. This directly impacts the performance of models relying on local spatial patterns. Although KPConv presents better robustness than traditional models, its performance is also degraded because of the lack of enough local information. Another important factor is the relative size and distribution of window features in the dataset. Windows take up a smaller part of the whole point cloud than the roofs. With the decrease of resolution, the number of points representing windows is greatly reduced, which causes class imbalance and more misclassification. This further leads to the decrease in F1-scores. Based on these observations, different building components should have different requirements for resolution. For the case of rooftop extraction, down sampling up to 1/16 resolution is acceptable, because the main geometric structure is preserved and the classification performance is still relatively high. This allows to reduce the size of the data and computational cost with a small loss of accuracy. In contrast, window extraction needs data with higher resolution to ensure strong performance. Resolution smaller than 1/4 causes a significant decrease in accuracy and is not suitable for high-precision window detection. Hence, point clouds of 1/4 or higher resolution are required for facade analysis and detailed energy modelling applications. This analysis highlights the importance of choosing appropriate resolution levels depending on the characteristics of the features. It also shows that although advanced models like KPConv improve robustness, the quality and density of input data are still essential factors for accurate feature extraction in the development of energy digital twins.

That said, resolution sensitivity is an important factor to consider, and the initial characteristics of a point cloud either amplify or mitigate its effects. All models degrade with down sampling, however KPConv consistently shows better resilience, especially for fine-grained features such as windows. KPConv is the most reliable solution when dealing with point clouds of heterogeneous quality or when down sampling is unavoidable. The impact of resolution reduction on

segmentation accuracy is highly modulated by the type of feature (fine vs. coarse) and the nature of the point cloud source (terrestrial vs. aerial).

6.4 Windows and rooftop energy modelling from the extracted building features

6.4.1 Energy Modelling with windows

For energy modelling in EnergyPlus, windows are represented as subsurface within building surfaces, and their geometric definition plays a critical role in calculating heat transfer, solar gains, and daylight penetration. When using aerial photogrammetric point clouds, several primary geometric inputs can be derived for windows, although with certain limitations due to the top-down acquisition perspective. The following are the key geometric parameters that were extracted and used for window energy modelling:

The most fundamental input is the window geometry, which includes the position, size, and shape of each window. From point clouds, windows can be identified on façade surfaces and represented as planar polygons. These polygons define the exact boundaries of the window and are used in EnergyPlus as subsurfaces within wall elements. Errors are directly related to solar gain and heat transfer calculations, so accurate window edge definition is important. Another important parameter is the area of the window. It is derived from the extracted polygon, and it is a major input in EnergyPlus because it defines the rate of heat transfer between the interior and exterior spaces. In general, larger window areas cause higher solar gains and higher heat losses and this parameter is very important in energy simulations. The orientation of the window is also important. It defines the orientation of the window (i.e. north, south, east, west) and it is calculated from the normal vector of the facade plane on which the window is placed. Orientation is directly related to the exposure to solar radiation and is used by EnergyPlus to calculate the incident solar energy on the window surface during the day and year. The closely related to orientation is the window tilt or inclination angle which is defined as the angle of the window surface with respect to the horizontal plane. For most façade windows this is generally near vertical (around 90 degrees) but can vary for inclined or non-standard architectural designs. This parameter controls the absorption of solar radiation by the surface. Another relevant input is the height of the window above ground level or its

relative vertical position within the building. The elevation values of the point cloud can be used to derive this. It impacts shading conditions from adjacent objects. It can impact wind exposure and convective heat transfer in advanced simulations. The window-to-wall ratio (WWR) can also be computed using the extracted window geometry and the corresponding façade surface area. This ratio is widely used in energy modelling to define the proportion of glazing in a building envelope and has a strong impact on both thermal performance and daylight availability.

In addition, window spacing and distribution across the façade can be derived from the spatial arrangement of window polygons. While EnergyPlus primarily requires individual window definitions, the overall distribution pattern can influence zoning decisions and aggregated thermal behavior. Table 31 below presents the geometric specifications which are essential for the windows energy simulations in EnergyPlus software.

Table 31 : Geometric specifications considered in the work for the windows energy simulations in EnergyPlus

Building geometry Parameter	EnergyPlus Object	IDF Field Name / Usage
Window Geometry (Polygon)	<i>FenestrationSurface:Detailed</i>	Vertex Coordinates (X, Y, Z)
Window Area	<i>Auto-calculated</i>	Derived from vertex coordinates
Window Orientation	<i>FenestrationSurface:Detailed</i>	Implicit from surface vertices (azimuth calculation)
Window Tilt Angle	<i>FenestrationSurface:Detailed</i>	Implicit from vertex geometry
Window Position	<i>FenestrationSurface:Detailed</i>	Vertex Coordinates (global positioning)
Window Height	<i>FenestrationSurface:Detailed</i>	Z-coordinates of vertices
Window Dimensions	<i>FenestrationSurface:Detailed</i>	Derived from geometry (not explicitly required)
Window-to-Wall Ratio	<i>WindowProperty:SimpleGlazingSystem or FenestrationSurface:Detailed</i>	Used in modelling assumptions or aggregated inputs
Façade Surface	<i>BuildingSurface:Detailed</i>	Base surface for window attachment

Façade Orientation	<i>BuildingSurface:Detailed</i>	Derived from wall vertices
Shading Context	<i>Shading:Building:Detailed</i>	Vertex coordinates of shading surfaces
Distance to Obstructions	<i>Shading:Building:Detailed</i>	Implicit in shading geometry
Window Construction	<i>Construction</i>	Assigned material layers (not from geometry, but required)
Glazing Properties	<i>WindowMaterial:SimpleGlazingSystem</i>	U-value, SHGC, Visible Transmittance
Surface Normal	<i>Internal calculation</i>	Derived from vertex ordering
Zone Assignment	<i>Zone</i>	Window linked to thermal zone via base surface

These geometric specifications were critical inputs for the energy simulation environment in EnergyPlus. To conduct energy simulations, the Input Data File (.idf) was prepared, including detailed window geometries and vertex definitions. Other mandatory inputs included window orientation, building geographical location, and material characteristics. The energy simulation also required the EnergyPlus Weather (.epw) file for Turin, which provides climate-specific data such as hourly temperature, solar radiation, humidity, and sky cover. These components are necessary for a precise simulation of the thermal performance of the building in different seasons. The simulations were run for a standard one-year Run Period (from January 1 to December 31). The windows were modelled with 2 mm thick clear glass material having U-Factor of $2.7 \text{ W/m}^2 \cdot \text{K}$, which is the rate of thermal transmittance. To simulate the fraction of incident solar radiation transmitted through the glazing, a Solar Heat Gain Coefficient (SHGC) of 0.6 was used. The outcome parameters obtained from EnergyPlus simulations included the Window Heat Gain Rate, representing the net thermal energy transferred into the building due to solar and conductive gains. Another critical output was the Window Transmitted Solar Radiation Rate, quantifying the portion of solar radiation entering through the glass. Both parameters were recorded on hourly, weekly, and annual scales to capture variations across seasons. Additionally, indoor versus outdoor temperature differences were analyzed to assess the insulation effectiveness and thermal comfort conditions for each window orientation type. Figure 26 below presents the annual analysis of the average solar gain and heat loss for each window orientation type.

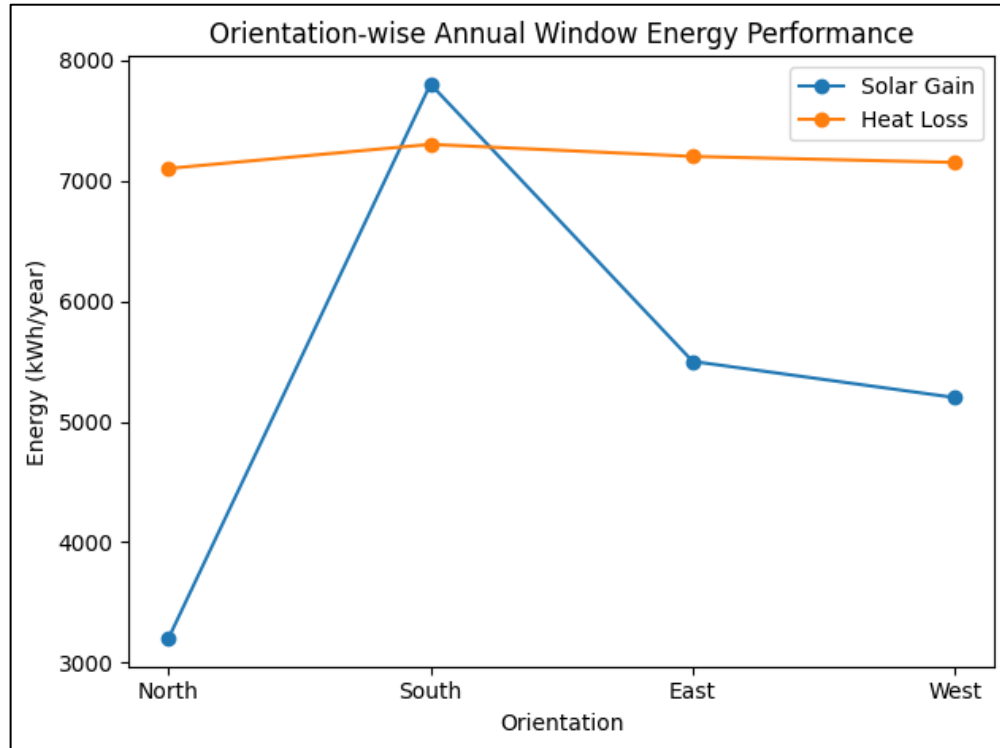


Figure 26: Analysis of the average solar gain and heat loss for each window orientation type (annual).

Higher solar gain values indicate that the window transmits more sunlight into the interior space, contributing to passive heating. This is particularly advantageous during the winter months, as it helps reduce the building's reliance on active heating systems. In the simulation results, the larger south-facing windows on floors 1 and 2 with dimensions $1.68 \text{ m} \times 3.33 \text{ m}$ showed notably higher solar gains due to their larger surface area and orientation, supporting winter-time thermal performance. Conversely, higher heat loss through windows reflects poorer insulation, where indoor heat escapes to the outside environment, increasing the building's energy demand, especially during colder periods.

The ideal window configuration is one that achieves a balance between high solar gain and low heat loss. In this case, windows with a high Solar Heat Gain Coefficient ($\text{SHGC} = 0.6$) and moderate U-Factor ($2.7 \text{ W/m}^2 \cdot \text{K}$) demonstrated the potential to maintain thermal comfort while reducing energy loads. Figure 27 below presents the overall analysis of the windows energy modelling.

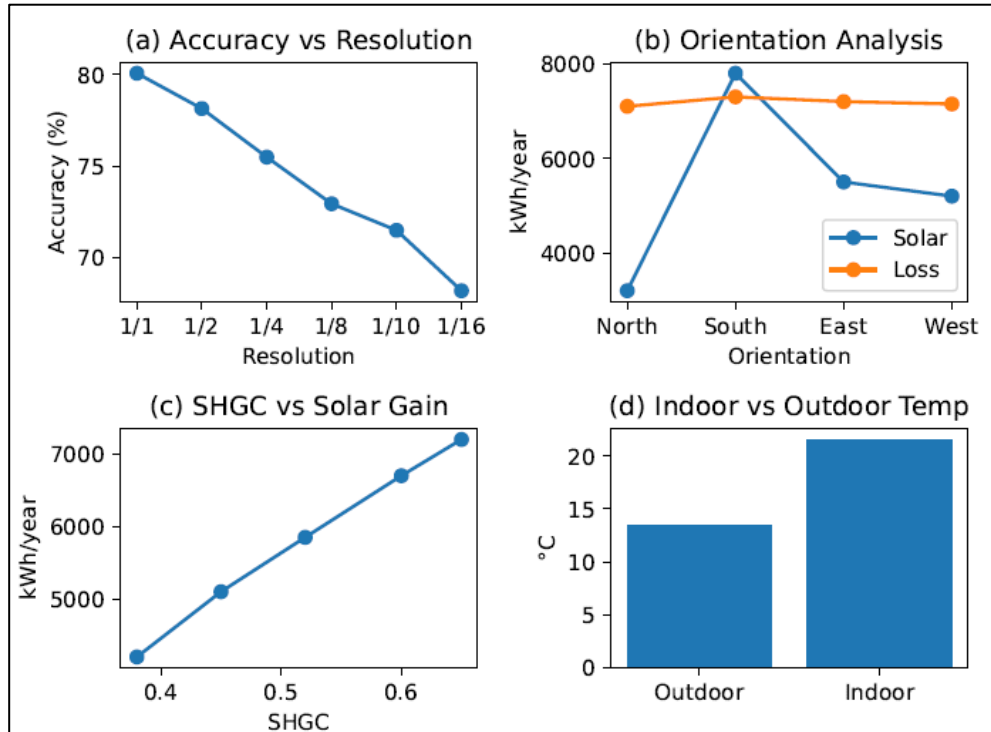


Figure 27: Overall analysis of the windows energy modelling.

The U-Value represents the rate at which heat is transferred through the window. A lower U-Value indicates better insulation performance, meaning the window resists heat loss more effectively. In this study, all simulated windows were assigned a U-Value of $2.7 \text{ W/m}^2\cdot\text{K}$, a standard for clear, single-pane glass. This level of insulation provides the essentials, but it also means that there will be a lot of heat loss especially during the winter months. The lower the U-Value, the less heat is lost from the building. This will make it more and more difficult to maintain indoor thermal comfort without an increased heating input. Solar Heat Gain Coefficient (SHGC) is the quantity of solar energy that may enter the building through the window and add to the heat inside the building. The higher the SHGC the more sunshine that gets into the building, which can be good or bad depending on the time of year. The simulation windows had a SHGC of 0.6, denoting moderate to high sun transmittance. This is most important in winter, as it will reduce the need for artificial heating and encourage passive solar heating. However, high summer SHGC may be undesirable due to excessive solar gain, which increases cooling loads and the risk of indoor overheating if not controlled by shading or glazing solutions. Windows with low U-value and seasonally tuned

SHGC are well suited to improve building energy efficiency. These thermal properties directly influence the accuracy of the energy demand calculations within the Energy Digital Twin models. By feeding detailed U-Value and SHGC data into simulations, the digital twin can better reflect real-world thermal performance, thus supporting data-driven decisions about retrofits and energy efficiency planning in cities.

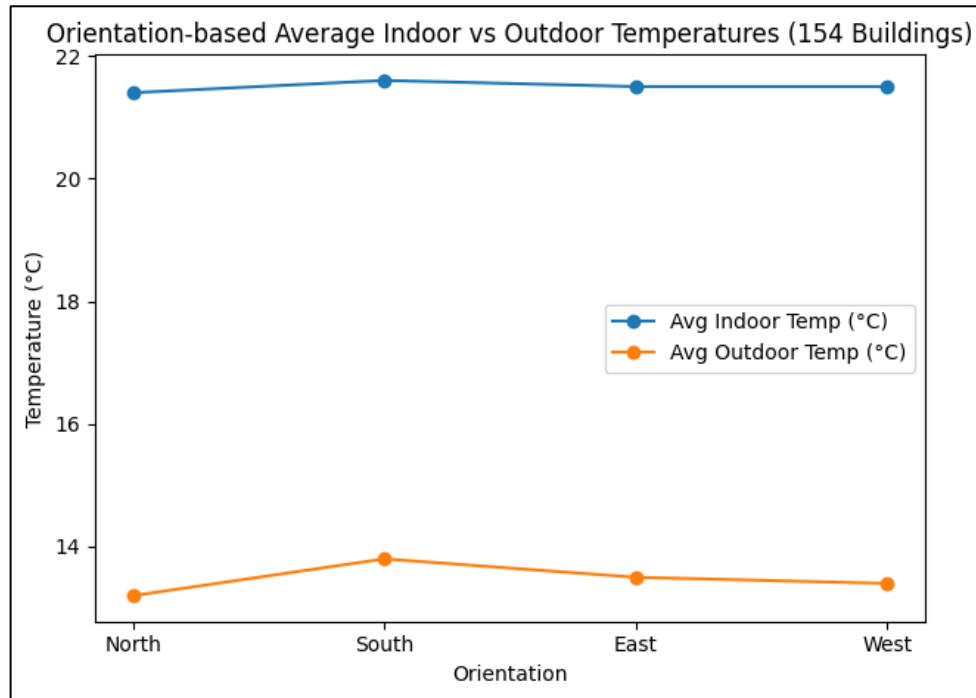


Figure 28: Indoor and outdoor temperature variations for windows on building energy efficiency for locality 1.

The difference between indoor and outdoor temperatures serves as a key indicator of window performance in terms of thermal insulation. This metric is especially useful when evaluating the effectiveness of window installations during varying seasonal conditions.

Figure 28 shows the average indoor and outdoor temperature for the 154 buildings of location 1 of Torino, classified according to the orientation of the windows (north, south, east and west). The indoor temperature in all orientations was ranged from 21.4 °C to 21.6 °C with almost constant value . This showed a controlled indoor thermal condition irrespective of the façade orientation. In contrast, the outdoor temperature shows little variation with orientation, ranging from 13.2°C (north facing) to 13.8°C (south facing). Windows facing south

receive more solar energy and are locally heated by the direct solar radiation; therefore, the outdoor temperature in their neighbourhood is higher. Partial sun exposure in the morning and evening corresponds to the intermediate values of east and west orientations. The outdoor temperature differs slightly but the indoor-outdoor temperature difference is similar for all orientations. This confirms that the driving force for conductive heat transfer through windows is mainly controlled by indoor setpoint conditions and outdoor climate and is largely independent of orientation. The results also confirm the previous findings that the heat loss through the windows is almost independent of the orientation, it depends on the thermal transmittance (U-value) and the temperature gradient and not on the solar radiation. However, solar gains are very orientation dependent, resulting in differences in the net energy balance. If the simulations show a large difference of the indoor and outdoor temperatures this means the windows are good at resisting heat transfer and either holding heat in during the winter or holding too much heat out during the summer. This is a sign of good thermal insulation, which means indoor comfort with less use of mechanical heating or cooling systems. If the temperature inside is very different to the temperature outside, it could mean your windows are not well insulated or are leaking air. These performance problems lead to the free movement of heat between the inside and the outside, increasing the demand for energy and decreasing comfort. In the EnergyPlus-based modelling performed in the present study, windows with U-Value of $2.7 \text{ W/m}^2\cdot\text{K}$ without added insulation features showed moderate temperature buffering. The smaller, older windows, especially those without glazing or sealing, however, tended to have smaller indoor-outdoor temperature differentials, implying potential energy inefficiencies. Figure 29 below presents the graphical analysis of the impact of indoor and outdoor temperature variations for windows

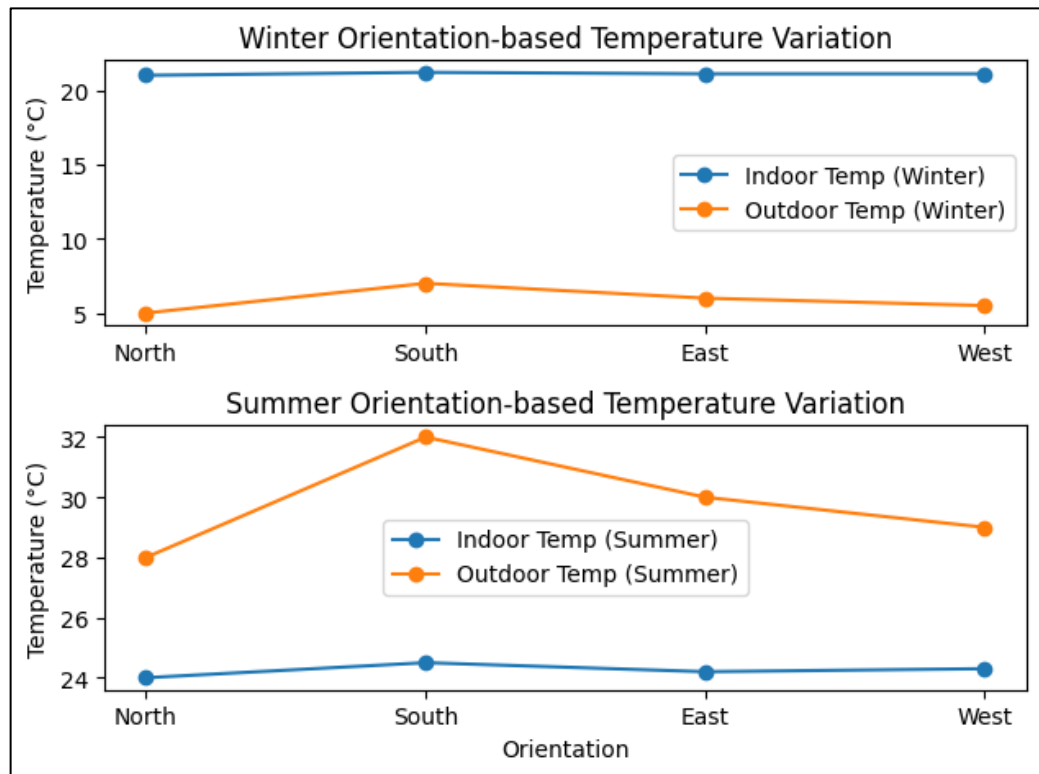


Figure 29: Analysis of the impact of indoor and outdoor temperature variations for windows.

During winter, outdoor temperatures vary significantly with orientation, ranging from 5°C (north) to 7°C (south). South-facing windows experience slightly higher temperatures due to solar exposure, while north-facing windows remain colder due to limited solar radiation. Indoor temperatures remain stable around 21°C, indicating effective heating control. The resulting temperature difference ($\Delta T \approx 14\text{--}16^\circ\text{C}$) is highest in winter, leading to maximum heat loss through windows. This confirms that winter conditions dominate annual heat loss in buildings. In summer, outdoor temperatures range from 28°C (north) to 32°C (south), showing strong orientation dependence due to solar radiation. South-facing façades receive the highest thermal load, while north-facing surfaces remain relatively cooler. Indoor temperatures remain controlled between 24.0°C and 24.5°C, demonstrating cooling system regulation. The temperature gradient is smaller ($\Delta T \approx 5\text{--}8^\circ\text{C}$), reducing conductive heat loss but increasing the risk of overheating due to solar gains.

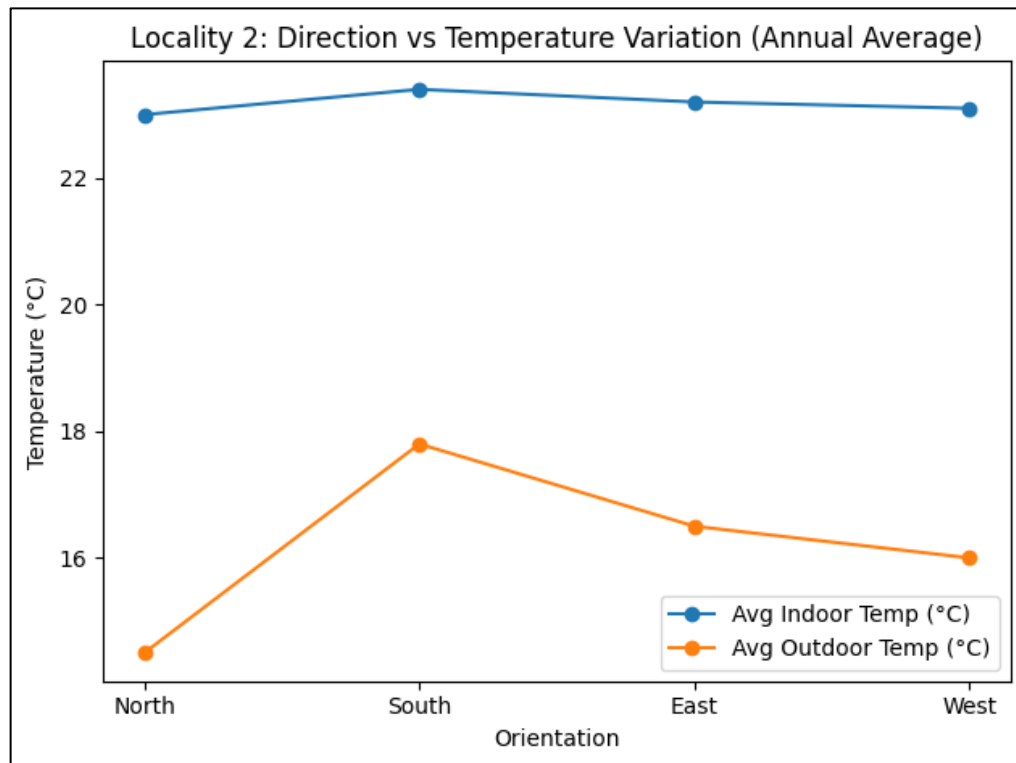


Figure 30 : Indoor and outdoor temperature variations for windows on building energy efficiency for locality 2

The figure 30 illustrates the annual average variation of indoor and outdoor temperatures across different window orientations (north, south, east, and west) for Locality 2 (184 buildings). The indoor temperature remains relatively stable across all orientations, ranging from 23.0°C to 23.4°C, indicating consistent indoor environmental control. In contrast, outdoor temperature shows clear orientation-based variation. South-facing windows exhibit the highest average outdoor temperature (17.8°C), followed by east (16.5°C) and west (16.0°C) orientations, while north-facing windows show the lowest value (14.5°C). This variation is primarily driven by differences in solar exposure, with south-facing façades receiving the highest annual solar radiation.

The resulting temperature gradient (ΔT) varies across orientations, being lowest for south-facing windows and highest for north-facing windows. This indicates that north-facing windows experience the highest heat loss potential, while south-facing windows benefit from reduced thermal gradients and increased solar gains.

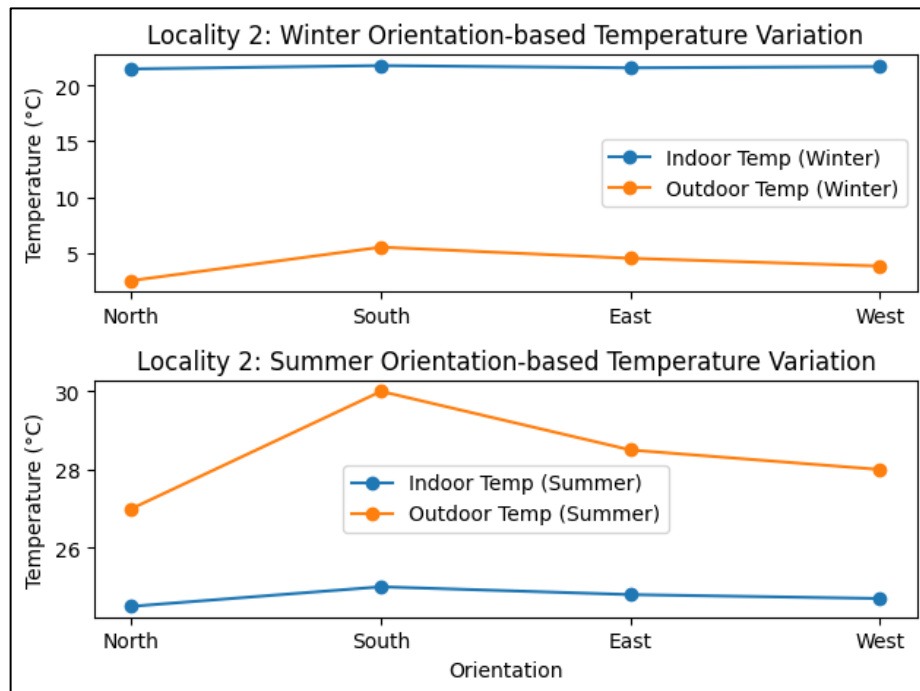


Figure 31: Seasonal variation of indoor and outdoor temperatures across orientations.

The figure 31 presents the seasonal variation of indoor and outdoor temperatures across orientations (north, south, east, and west) for Locality 2 (184 buildings), highlighting differences between winter and summer conditions.

During winter, outdoor temperatures vary significantly with orientation, ranging from 2.5°C (north) to 5.5°C (south). South-facing windows exhibit slightly higher temperatures due to increased solar exposure, while north-facing windows remain the coldest. Indoor temperatures remain stable between 21.5°C and 21.8°C, indicating controlled heating conditions. The resulting temperature gradient ($\Delta T \approx 16\text{--}19^\circ\text{C}$) is higher than Locality 1, leading to increased heat loss. In summer, outdoor temperatures range from 27°C (north) to 30°C (south), showing a clear orientation dependency driven by solar radiation. Indoor temperatures are maintained between 24.5°C and 25.0°C, reflecting cooling system regulation. The temperature gradient is smaller ($\Delta T \approx 3\text{--}6^\circ\text{C}$), indicating reduced conductive heat loss but increased solar-driven heat gains.

6.4.2 Energy Modelling with rooftops

The goal of this experimentation was to estimate the annual solar and potential from aerial photogrammetry point clouds. The solar and PV potential estimated based on the surface geometry and orientation of the building rooftops in the selected localities in the city of Torino. The solar and PV potential was estimated from photogrammetry point clouds for the identified building surfaces as represented in Figure 32 below.

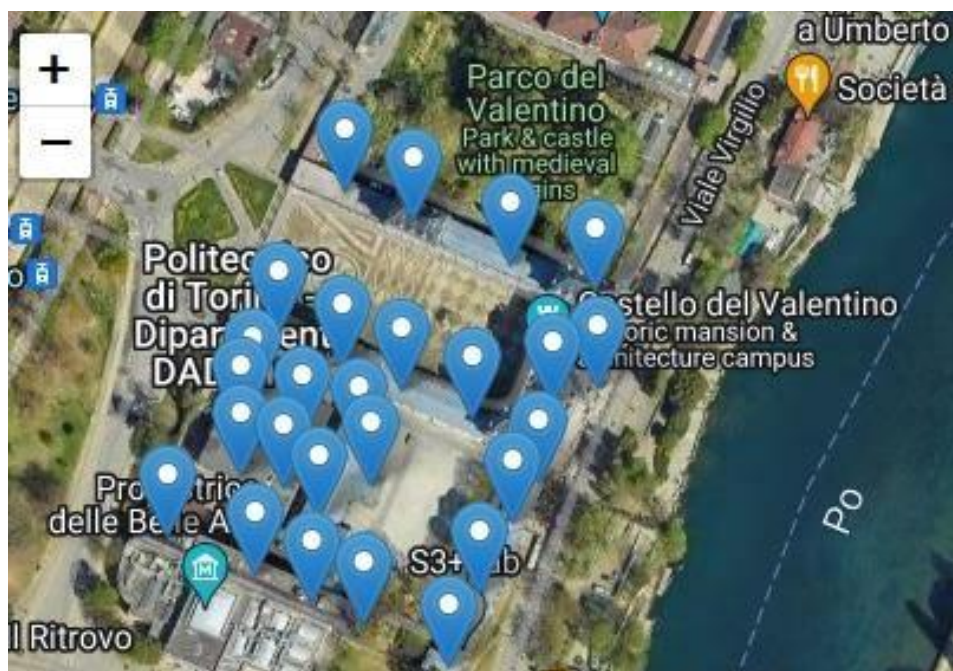


Figure 32: Building roof surfaces identified for solar potential potential from photogrammetry point cloud of one of the test site.

First, the 3D point clouds generated from aerial photogrammetry are processed to identify building surfaces suitable for PV installation. These surfaces are then analysed for their tilt, orientation, and exposure to sunlight throughout the day, factors that significantly impact the potential energy generation. For the photogrammetry point cloud, the building rooftop surfaces were identified for PV estimation. This high number of surfaces is attributed to the high density of the photogrammetry point cloud, which allowed for the detection of small and complex surfaces that may have been missed by LiDAR.

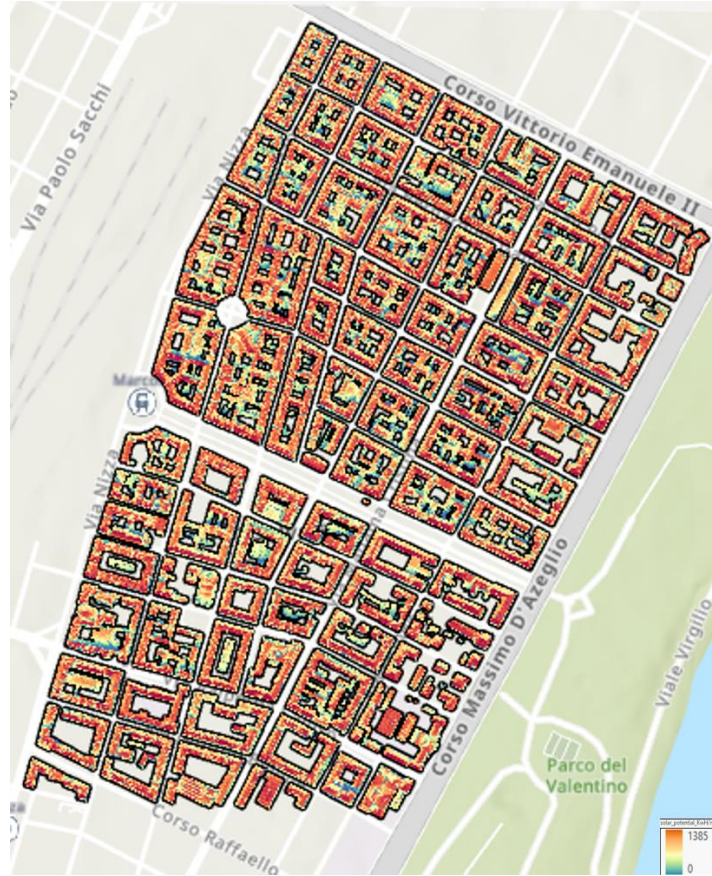


Figure 33: Solar Potential estimate for San Salvario, Torino, Italy.

The Solar potential was estimated for the building rooftops with the 'Area Solar Radiation' Tool in ArcGIS pro with consideration of the important parameters as mentioned in Section 3.2. The annual solar potential of the locality with 154 buildings was found to be 20,654,014.78 kWh for the net building rooftop area of approximately 20679.42 m². Table 32 summarises the analysis results for the solar potential estimation.

Table 32: Analysis results for the solar potential estimation for San Salvario locality (locality 1).

Experiment case	Number of buildings	Solar Potential (kWh/m ²)	Available rooftop area (m ²)
All rooftops	154	998.7715	20679.42
North Facing rooftops	37	751.8312	1971.82
Rooftops with an area < 200 m ²	82	863.8721	3218.79
Rooftops with Solar Potential < 800 kWh/m ²	93	842.3214	4268.79
Available rooftops for Solar Potential	67	976.1583	13747.90

The results from the Solar Energy analysis have been represented in Figure 33 with the estimation of solar estimation of all 154 buildings from the locality with an average solar potential of 998.77 Kwh/m². The solar potential data for the 154 buildings in this study reveals a significant gap between the total theoretical capacity and what is realistically achievable when geospatial constraints are applied. At the baseline, the total rooftop area exceeds 20,000 m² with an average potential of nearly 1,000 kWh/m², yet a closer look at orientation and size shows why much of this area is unsuitable for high-efficiency energy production. For example, the 37 north-facing rooftops have the lowest energy yield of about 752 kWh/m², which is by 25% lower than the general average. This is because north-facing slopes in the northern hemisphere receive much less direct solar radiation and are more subject to self-shading. Moreover, the analysis also shows strong fragmentation of the urban fabric, with 82 buildings (more than half of the total number of buildings) having individual rooftop areas smaller than 200 m². These small roofs do add to the total count, but with a total area of only 3,218 m² there is very little space for meaningful panel arrays and they probably come with higher installation costs per square meter. From a technical perspective, selecting “Available rooftops for Solar Potential” is a conscious choice to place more emphasis on building quality and efficiency than on quantity. The filtered subset only contains 67 buildings, but still has more than 13,747 m² of usable area and a high potential of 976 kWh/m². The system then discounts the 93 buildings that don’t meet the threshold of 800 kWh/m², effectively removing low performance surfaces that would otherwise drag down the average return on investment of the

entire project. This filtering logic is important for real world applications as it identifies the “prime” surfaces that provide the best mix of large unobstructed area and high solar exposure. When comparing this optimised subset to the total rooftop case we find that we are able to capture about 66% of the total available area with only 43% of the buildings. This suggests that the energy digital twin should focus its simulation efforts on these high-yield structures, as they provide the most reliable data for predicting a city or campus-wide transition to renewable energy without the technical and financial waste of installing systems on small, shaded, or poorly oriented roofs.

Table 33: Analysis results for the solar potential estimation for SkyScraper locality (locality 2).

Experiment case	Number of buildings	Solar Potential (kWh/ m2)	Available rooftop area (m2)
All rooftops	184	1002.4518	24856.12
North Facing rooftops	44	748.6215	2315.45
Rooftops with an area < 200 m2	98	855.1247	3824.6
Rooftops with Solar Potential < 800 kWh/ m2	110	838.5512	5112.34
Available rooftops for Solar Potential	80	982.741	16540.85

The results for this larger dataset confirm the trends seen in the previous study but provide a more robust view of the urban solar capacity. By increasing the sample to 184 buildings, the total available rooftop area rises to approximately 24,856 m². The average solar potential is steady at 1,002 kWh/ m2, very realistic for Torino’s latitude and common urban shading patterns. However, the data shows that a significant part of the building stock is technically inefficient for solar energy. For example, 44 buildings (24%) are orientated to the north with a lower potential of 748.6 kWh/ m2, under the common viability threshold of 800 kWh/ m2 due to the poor orientation. The filtering process for "Available rooftops" shows that quality over quantity is key for an Energy Digital Twin. Although the total number of buildings is 184, only 80 buildings (approx. 43%) are considered suitable for solar installation. These buildings constitute the majority of the usable space, 16,540 m2 with a high energy yield of 982.7 kWh/ m2. We exclude 110 buildings of low potential or too small (less than 200 m2)

and thus remove surfaces where installation would be difficult or economically inefficient. This finding indicates that about two thirds of the total energy potential of a typical Torino district can be exploited by targeting less than half of the buildings, i.e. those with larger, unobstructed and south-oriented roof planes.

A comparison of table 32 and table 33 shows that the results are very consistent, even when the number of buildings increases from 154 to 184. In both circumstances, only about 43% of the buildings are “Available” for solar, but these buildings constitute about 66% of the total rooftop area. This consistency proves that the urban layout of Torino follows a strict pattern where a small number of large, well-positioned roofs provide most of the energy potential. The fact that the average solar potential stays nearly the same, around 1,000 kWh/ m², across both datasets confirms that the research is not seeing random luck, but a predictable physical reality of the city's design. The main reason for the difference between the "All rooftops" and "Available" groups is the physical environment, specifically shadows and roof size. In both tables presenting the quantitative results, about 60% of buildings fall below the 800 kWh/ m², limit because they could be trapped in the shadows of taller neighbours, which is a common problem in dense urban cities like Torino. Furthermore, over half of the buildings have roofs smaller than 200 m², which are often too cluttered with vents or chimneys to be useful. By filtering out these low-performing and small roofs, the research identifies the "prime" surfaces that offer the best return on investment. This reasoning shows that for an Energy Digital Twin to be accurate, it must focus on these specific geospatial factors rather than just looking at the total number of buildings.

From the quantitative results, over 53% of the buildings have roofs smaller than 200 m². From a geospatial perspective, these small roofs are often cluttered with chimneys, vents, or elevator shafts, making the actual "net" area even smaller than what the 3D model shows. This is why the filtered "Available" rooftops are so critical, they represent the larger, flatter surfaces that are easier to simulate and develop. In both studies, roughly 60% of the buildings fall below the 800 kWh/m² threshold. This is a "critical limit" for Torino. Because the city is dense, the lower floors or smaller buildings are permanently trapped in the shadows of larger ones. The fact that the "Available" buildings consistently account for exactly 43% of the count but 66% of the area is the most important takeaway. It means that the Energy Digital Twin does not need to simulate every single building with high detail. Instead, it can focus its computational power on this 43% of "prime" rooftops to capture most of the city's energy potential.

6.5 Visualisation for EDTs

The visualization stage is the final and most critical component of the Energy Digital Twin (EDT) pipeline, as it acts as the interface between complex datasets and human decision-making. The previous stages deal with data acquisition and simulation. The visualisation layer uses the numeric results stored in the GeoDB and visualises them in a spatial context. In this study, we evaluated several platforms for their ability to handle large 3D datasets, such as point clouds and LoD3 building models, while displaying time-series energy data. The choice of the visualisation tool depends mainly on the target audience, specialised researchers who need detailed analysis or city planners who need a user-friendly overview.

ArcGIS Pro is one of the main tools for professional-grade visualisation. It is a desktop-based Geographic Information System (GIS) and provides a robust environment for managing the “heavy” geospatial data generated in the earlier steps of the research. I find ArcGIS Pro is very good at overlaying 3d building features with the usual 2D maps, and also allows the researchers to conduct spatial queries within the visual interface. For example, it allows a user to visually filter buildings based on solar potential or window to wall ratio. However, from a critical point of view, although ArcGIS Pro is a powerful software for scientific analysis, it is a heavy software that requires a good computer and a paid license, which can limit its use for sharing results with the general public or local stakeholders.

The problem of accessibility was handled by exploring web based platforms like Caesium and Mapstore. Caesium is a JavaScript library for building world-class 3D globes and maps. Caesium is open source. It works very well for EDTs because it uses "3D Tiles", a format that allows large point clouds and complex building models to stream smoothly in a standard web browser. This means that a city planner can see the energy performance of an entire district on a laptop, without having to install any special software. That is complemented by Mapstore, which offers a framework for building interactive dashboards. The integration of Mapstore with the GeoDB enables the research to display the 3D models along with 2D charts and graphs that are updated in real time. The combination is very realistic for urban energy management, since it offers high quality 3D visualisation and easy-to-read performance metrics. The next step in EDT visualisation is Game Engines like Unity or Unreal Engine for high-end, immersive experiences. They provide a level of visual realism that traditional GIS

software can not match, featuring realistic lighting, weather effects, and smooth first-person navigation through the city. In this research, the game engines allow for "what-if" scenarios, for example, walking down a street and seeing how shadows from new buildings affect the solar potential of existing rooftops. But the truth is, game engines are steep to learn. They are not conceived natively for GIS data. This means that the translation of building attributes from a GeoDB to a game engine is a great effort and can sometimes lead to a loss of data precision. The visualisation of an EDT is not a "one-size-fits-all" solution. For the internal research and data heavy analysis phases, ArcGIS Pro is the best option, and for sharing the twin with external users via the web, Caesium and Mapstore are the most practical and scalable way. They look good, but for the moment they are best used for specialised presentations or detailed interactive simulations where immersion is more important than raw data processing . Through the integration of these different tools, the research ensures that the Energy Digital Twin is not only a set of numbers but a functional, visual tool that can be used to guide real-world energy improvements in the city of Torino.

Figure 34 below presents the operationalisation of the semantic data model of one of the small area from Torino into a Urban Digital Twin interface. It is the practical synthesis of the algorithmic classification and ontological structuring above. It shows how the raw data processed by the ensemble models and KPConv is transformed into a spatially explicit visualisation tool. In this setting, urban features are not just geometric meshes, but semantically enriched objects, enabling multidimensional analysis within a single GIS-based framework.



Figure 34: ArcGIS Pro GeoDB layers organization and 3D visualization

The interface panel on the right validates the research's LOD hierarchy, showing the active management of layers ranging from LOD 0 (DTM and World Imagery) to LOD 4 (Energy data). The central visualization utilizes a color-coded thematic map based on "ALTEZZA_VO" (building height), illustrating how geometric attributes derived from the point cloud classification are queried to analyze urban density. By maintaining the "is composed by" and "contains" relationships established in the schema, the system allows the user to transition from a macro-scale view of the district down to the granular, component-level details of individual roofs and building parts at LOD 2. Ultimately, this platform serves as the analytical "output" of the PhD pipeline, specifically through the integration of the LOD 4 Energy data layer. By correlating the physical characteristics identified in the segmentation stage such as specific rooftop geometries with dynamic performance metrics like solar potential and heat transmissivity, the interface becomes a robust decision-support system. This enables researchers and urban planners to simulate the impact of architectural interventions on district-wide energy efficiency, effectively bridging the gap between computer vision, data modeling, and urban sustainability.

Chapter 7

Discussions, Implications and Scope of the research

This chapter discusses the primary conclusions of the research about the construction of an Energy Digital Twin (EDT). The emphasis is on the impact of geospatial data, processing techniques, and energy modelling decisions on the accuracy and reliability of EDT development and its implementation in urban environments. The discourse emphasises the significance of precisely depicting essential architectural components, including windows and roofs, the ramifications of data resolution on the extraction of building features, and the integration for extensive urban energy modelling for an EDT. The chapter delineates the constraints of the existing methodology and specifies avenues for prospective enhancements in EDT development.

7.1 Discussion on the research outcomes

The development of an Energy Digital Twin (EDT) based on geospatial datasets must be framed primarily by the requirements of building energy modelling rather than by the availability or convenience of data sources. In this context, the accurate representation of building envelope components is fundamental, and among these, windows and roofs emerge as the most critical elements due to their dominant role in heat transfer and solar radiation exchange. Windows govern solar gains and conductive losses. Roofs are major contributors to thermal exposure and solar potential. Thus, any EDT framework that does not explicitly prioritise the correct extraction and representation of these components may introduce systematic errors in energy simulations. This observation is well supported in the literature, where façade-related parameters, especially window-

to-wall ratio (WWR), have been shown to significantly influence heating and cooling loads, often resulting in deviations of 10–30% when inaccurately represented (Nouvel et al., 2017; REINHART et al., 2013). The results obtained in this study are consistent with these findings and further highlight that the reliability of EDT outputs is strongly dependent on the level of geometric detail captured for façade elements.

The minimum set of inputs required for simulation tools like the EnergyPlus building energy simulation software include geometric descriptors (surface area, orientation, tilt and spatial position of windows and roofs) and material properties (U-values and Solar Heat Gain Coefficients (SHGC)). Roofs can be modelled by relatively simple planar geometries, whereas windows require a more detailed description, as they are smaller, more variable and have a direct interaction with solar radiation. This distinction is important when translating geospatial data into simulation-ready models because it means different parts of a building require different levels of accuracy. The results of this study clearly demonstrate that rooftop features can be extracted with relatively high reliability even at reduced point cloud resolutions, whereas window detection and delineation degrade significantly with reduction of resolution. This non-uniform sensitivity implies that windows and roofs have to be considered as important modelling requirements rather than as by-products of generic point cloud processing workflows.

The generation of EDTs from aerial photogrammetry is based on the integration of multiple geospatial datasets providing different but interdependent layers of information. The main data source is high-resolution aerial imagery, which is processed to produce dense three-dimensional point clouds by means of aerial photogrammetry. The point clouds represent the geometric skeleton of the EDT and make it possible to reconstruct building shapes and identify structural elements. However, the utility of this data set is intrinsically tied to the spatial resolution and point density of the data. The results show that the classification accuracy gradually decreases with down sampling, from about 80% at the full resolution to about 68% at the lowest tested resolution. This reduction is moderate on a global scale, but its effect on certain features, especially windows, is disproportionately significant.

Point clouds provide geometric information, but it is also necessary to have Digital Elevation Models (DEMs) and Digital Surface Models (DSMs) to provide a consistent reference height and distinguish the ground from the above-ground

structures. This dataset enables the normalisation of point cloud data and therefore the separation of buildings from terrain and vegetation. Building footprint data is often available from cadastral or GIS data and offers an additional constraint to improve geometric consistency and reduce reconstruction errors. Footprints offer a solid two-dimensional basis for the three-dimensional representation, thus enabling the calculation of façade areas and the estimation of WWR, both required for energy modelling. Semantic classification is another important part of data integration. Using machine learning or deep learning methods, each point of the cloud is labelled as different building components such as roof, wall, window etc. This semantic layer is needed to distinguish the different parts of the building envelope and to apply the right thermal properties in simulation. However, the accuracy of semantic classification heavily relies on the quality of input data and the robustness of classification algorithm. The application of the KPConv neural network for point cloud classification in this study demonstrates the potential of deep learning methods to achieve high classification accuracy in complex urban environments. However, results show that this performance degrades for decreasing resolutions, especially for small scale features.

The point density does not have the same effect on the accuracy of the classification for different building elements. Rooftops are usually large and planar and are relatively insensitive to down-sampling with high F1 scores even at lower resolutions. However, for the windows, the F1-score sharply drops, up to 30 percentage points reduction for the lowest resolution cases. This is because the number of points representing each window is small and more likely to be missed or misclassified as the data becomes sparse. This is also evident in the literature where small-scale architectural features have always been reported as the most difficult features to detect in point cloud data (S. Chen et al., 2023). This study adds to this understanding by quantifying the direct effect of such detection errors on energy simulation outputs. These results have important implications for the development of EDT. The window size affects the solar gain and heat loss directly. Thus, non-linear propagation of errors occurs when windows are extracted to estimate energies. The results indicate that underestimation of window area by 10 % can lead to differences of 500–600 kWh/year in solar gain. This error level is important, especially when summed up for the whole building or urban district. This illustrates the huge importance of maintaining a high geometrical accuracy for façade elements. However, the relative stability of the rooftop extraction means that the measurements related to the energy potential of rooftops are less sensitive to the resolution of the point cloud. The pipeline for extracting EDTs from point clouds consists of segmentation,

classification and geometric reconstruction. RANSAC based plane detection and other rule based geometric methods are good at detecting large flat surfaces like roofs, but not good at capturing the complexity of facades and windows . However, machine learning methods, while better able to exploit statistical patterns in data, are generally based on handcrafted features and may have difficulties in generalising to different urban contexts. Deep learning methods, such as KPConv, are a great progress as they enable end-to-end learning of features directly from raw point cloud data. But as this study shows, their performance is still limited by the quality and density of the input data.

The apparent resolution sensitivity of window detection indicates that uniform down sampling strategies are not appropriate for EDT applications. Instead adaptive or multi-resolution approaches should be considered, where higher point densities are preserved in regions of interest, in particular façades, while lower densities may be acceptable in less critical areas such as roofs or ground surfaces. This method is consistent with the general notion of Level of Detail (LoD) in 3D city modelling, where different levels of geometric complexity are used for different applications (Biljecki et al., 2016; Biljecki & Ohori, 2015). For energy modelling purposes LoD2 may be sufficient for roof-based analysis but LoD3 or higher is required to accurately represent windows and other façade features. While aerial photogrammetry has benefits with respect to coverage and scalability, it is inherently limited for EDT applications. The top-down acquisition geometry makes vertical surfaces less visible, resulting in incomplete or noisy facade reconstructions. This limitation is especially problematic for window detection because it leads to missing or distorted features that cannot be reliably recovered. This problem is exacerbated by occlusions from vegetation or neighbouring buildings which lead to gaps and inconsistencies in the data. These challenges have been well documented in studies comparing aerial and terrestrial data sources, with terrestrial LiDAR often shown to produce better façade detail with its horizontal perspective of acquisition (Pu & Vosselman, 2009). But land-based data collection tends to be more resource intensive and less scalable and There will be a trade-off between quality and coverage.

Another disadvantage of geospatial datasets is the absence of direct data on material properties. Important parameters for energy simulations such as U-value and SHGC cannot be derived from the point cloud data and have to be inputted with assumptions or standard values. This adds an extra level of uncertainty to the EDT, because different values of these parameters can have a large impact on the results of the simulation. The findings of this study indicate that small differences

in SHGC, on the order of 0.05, can translate into several hundred kWh per year in solar gain. This sensitivity underlines the importance of careful selection and validation of material properties, and the potential benefits of integrating other data sources such as building databases or in situ measurements. The development of EDTs is further complicated by the interaction between geometric, material and environmental inputs. These inputs do not function in isolation, but rather interact to magnify or diminish their individual effects. For instance, the effect of window orientation on solar gain depends on the SHGC of the glazing and the climate conditions of the location. Likewise, heat loss through the building envelope is governed by the joint effect of U-values and temperature differences between indoor and outdoor conditions. The results of this study illustrate these interactions and how relatively small changes in input parameters can result in significant differences in overall energy performance. This underscores the necessity of treating the EDT development as a multi-dimensional problem, where uncertainties in different inputs need to be treated and propagated carefully through the modelling process. This comparison of locations also illustrates the sensitivity of energy simulations to the environment and data quality. Differences in outdoor temperature, solar radiation and urban morphology can affect the balance between solar gains and heat losses. The observed differences in energy performance of the two localities are consistent with the differences in climatic conditions and the potential shading effects. However, these differences also depend on the accuracy of the underlying geometric data, in particular in the case of windows. This highlights the importance of local calibration for reliable urban energy modelling and the limitations of generalised assumptions for achieving accuracy.

To comprehend, the results of this study indicate that the development of Energy Digital Twins is fundamentally constrained by the quality, resolution and completeness of geospatial data. Aerial photogrammetry is a powerful and scalable method to capture urban geometry. Its deficiencies in reconstructing the façade and the lack of data on the materials are considerable obstacles, however. Results show that the roof modelling is relatively robust while the window modelling is the main source of uncertainty. This distinction has important consequences for strategies of data acquisition and processing and points to the need to improve the accuracy of façade representation. Future work should therefore consider the integration of multiple data sources, such as combining aerial photogrammetry with terrestrial LiDAR or oblique imagery to improve façade detail. Further enhancement of accuracy and efficiency could also be achieved through the development of adaptive processing techniques, which

would preserve high resolution in critical areas and reduce the data volume in other areas. Finally, more detailed material and operational data can help to reduce the uncertainty of energy simulations and to obtain more realistic representations of building performance. In the end, the accuracy of an Energy Digital Twin is not a matter of the capabilities of simulation tools such as EnergyPlus building energy simulation software, but rather the degree to which the geospatial data underneath it can capture the physical characteristics of the built environment. The results of this work point to the need for a more integrated and data-driven approach to EDT development, where energy modelling requirements are explicitly taken into account at every step of the workflow, from data acquisition, processing, to simulation.

7.2 Implications and Scope of the work

The findings of this study add to the increasing field of Energy Digital Twin (EDT) development, especially in the integration of sets of geospatial data and advanced point cloud processing techniques in energy simulation processes. In the field of urban modelling, there is a growing movement in recent years towards data intensive and spatially explicit representations of the built environment. This change leverages detailed geometric and semantic information to improve the accuracy of simulation-based analysis. However, the direct integration of point clouds in energy modelling frameworks is still rather limited despite the large number of studies on the use of point clouds for building reconstruction and classification. This work fills this gap by developing a structured workflow connecting point clouds from aerial photogrammetry with semantic classification and physics-based simulation environments like the EnergyPlus building energy simulation software. In doing so, it places itself within a broader move from static and reductive representations of buildings to dynamic and data-driven urban energy models.

An important finding of this study is the importance of high-resolution point cloud data for accurate geometric reconstruction in EDT applications. The results indicate that the reliability of the extracted building features, especially the façade elements such as windows, is directly impacted by the point density and the spatial resolution. Large-scale structures such as roofs can be reconstructed with a relatively high accuracy even at reduced resolutions, while small and detailed features are very sensitive to the sparsity of the data. This result implies that a single approach to data generalisation cannot be applied for EDT development, as different building components have different requirements for geometric fidelity.

This highlights the importance of high-resolution datasets in terms of reliable energy modelling results in their practical applications, especially when facade-driven parameters such as window-to-wall ratio and solar exposure are involved. The study also highlights the significance of deep learning techniques in point cloud classification for EDT generation. Deep learning models such as KPConv neural network for point cloud classification outperform traditional rule-based or machine learning techniques in capturing complex spatial patterns and differentiating building elements. This is especially important in heterogeneous urban environments, where the variability of building morphology and data quality can be a hindrance for conventional approaches. However, the results also indicate that the performance of these models is intrinsically tied to the properties of the input data, e.g., resolution, noise and completeness. Thus, deep learning improves classification accuracy, but does not eliminate the dependence on high quality geospatial inputs. This highlights the need to consider algorithmic and data driven aspects in EDT development rather than treating them as separate entities. This research has significant implications for the value of the integration of Geographic Information Systems (GIS) within the EDT framework. GIS is a key tool for the organization, management and visualisation of spatial data at different scales, allowing the integration of geometries from point clouds with ancillary datasets such as building footprints, elevation models and climate data. The integration enables the generation of models that are ready for simulation as well as the interpretation and communication of results. For example, GIS-based visualisations allow for the spatial identification of buildings or sites with high solar potential or energy consumption, which in turn enables more informed decision-making processes. In addition, the possibility of carrying out analyses at different scales, from single buildings to whole districts, makes EDTs more applicable in urban planning contexts.

The implementation of the conceptual framework presented in this thesis focuses on building the geospatial and semantic foundation for an operational EDT solution. The developed EDT workflow system is therefore best understood as an EDT foundation capable of supporting dynamic operation in the future, but not yet there. The periodic updates of EDT system are possible by reprocessing new geospatial datasets and environmental inputs, but a fully automated, real-time feedback loop between the physical environment and the virtual model falls outside the scope of this work. In terms of digital twin maturity, the current system sits at an intermediate level: bidirectional communication and continuous synchronisation are next steps, not current features.

The combination of geospatial data, machine learning, and physics-based simulation represents a significant advancement in the development of Digital Twins for energy systems. This integration offers a more comprehensive description of the built environment by considering the geometric accuracy, semantic features richness and physical world behaviour simultaneously. This research shows that the integration of the energy simulation tools in the EDT results in a better consistency between geospatial data and energy simulation outputs and thus a better reliability of the EDT. At the same time, it also shows the interdependencies between different data types and modelling components, thus stressing the need for coordinated data acquisition, processing, and validation procedures.

From an application perspective, the framework developed in this research has several important implications for urban energy planning and policymaking. As cities embark on adopting ambitious energy efficiency, carbon reduction and climate resilience targets, tools are needed to provide granular and scalable assessments of building energy performance. This need is met by the framework for EDT presented here which allows the generation of high resolution, spatially explicit energy models that can support a range of planning activities. One key application is to identify buildings that are energy inefficient with high spatial resolution. This allows us to correlate some geometric characteristics (e.g. window area, orientation) with the results of energy simulation and to identify individual buildings or building elements responsible for a significant part of energy consumption. Moreover, the accurate reconstruction of rooftop geometries enables the assessment of the solar energy potential at building and district level. This is of particular interest in the context of renewable energy integration where rooftop photovoltaic installations represent a large opportunity for decentralised energy generation. Such a possibility of assessing the solar potential based on detailed geometrical and environmental data allows a more effective planning and prioritisation of such interventions. Also, the framework can be used to support planning of building retrofits by means of data-driven insights into the thermal performance of the building envelopes. The impact of different parameters (e.g. window properties, levels of insulation) can be quantified, enabling decision makers to assess the potential benefits of various retrofit strategies before they are implemented.

A further important application is the evaluation of alternative energy scenarios for neighbourhoods or urban districts. The EDT brings together the many data sources and simulation outputs into a single framework and makes it

possible to explore different policy or design scenarios such as changes in building materials, energy systems or urban form. This is particularly useful for long-term planning where the impacts of different interventions need to be assessed under different environmental and socio-economic conditions. Further, higher accuracy of geometric and semantic data supports improvement of city-wide energy inventories that is vital to assessing progress towards sustainability goals and guiding policy. However, some factors limit the scope of the present research that define directions for future work. A major limitation is the use of aerial photogrammetry as the main data source. This inherently limits the quality of façades reconstruction due to occlusions and angles of view. This affects the detection accuracy of the windows and hence the reliability of the energy simulations. Future research should therefore explore the combination of more data sources such as terrestrial LiDAR or oblique imagery for better representation of the façade. Also, the modelling procedure is uncertain due to the assignment of material properties as per standard assumptions. The EDTS could be improved by more detailed, site-specific material data, for instance through databases or field measurements.

Another aspect to be further investigated is the consideration of dynamic aspects such as occupant behaviour and operational schedules that have not been explicitly considered in this study. The current framework is based on the physical properties of the buildings. Nevertheless, these dynamic factors can have a substantial impact on the energy consumption and should be taken into account in future EDT models. Finally, scalability of the framework to larger urban areas, and computational efficiency are important considerations, especially for real-time or near-real-time applications. This doctoral research demonstrates that the combination of high-resolution geospatial data, advanced point cloud processing and energy-based simulation provides a solid basis for the development of Energy Digital Twins. In addition to the methodological advances, this work has implications for urban energy planning and decision-making. At the same time, the identified limitations point to the need for continued research to address challenges related to data quality, integration, and model complexity, thus pushing the state of the art in EDT development further. The implications of the different aspects of the research undertaken are set out below in Table 34.

Table 34: Implications of the different aspects of the research.

Aspect	Key Implications	Stakeholders	Uses / Applications
Point Cloud Quality	High-resolution data is important to get accurate building shapes, especially windows	Researchers, GIS Experts, Urban Modelers	Better 3D building models for energy analysis
Windows and Rooftops extraction	Windows strongly affect energy loss and solar gain; roofs are easier to detect and more stable	Energy Engineers, Architects	Accurate calculation of heat loss and solar energy potential
Deep Learning Methods	Deep learning gives better results than traditional methods but needs good data	AI Researchers, Remote Sensing Experts	Automatic detection of building parts like roofs and windows
GIS Integration	GIS helps combine different data and analyze it at different scales	Urban Planners, GIS Specialists, Authorities	Mapping and visualizing energy performance of buildings
Energy Simulation Link	Connecting geometry with simulation improves energy estimation accuracy	Energy Modelers, Analysts	Running building and city-level energy simulations
Urban Energy Planning	EDT helps in making better planning decisions based on data	City Planners, Policymakers	Finding inefficient buildings and planning improvements
Solar Energy Potential	Accurate roof data helps estimate solar energy generation	Renewable Energy Experts, Engineers	Planning rooftop solar installations

Building Retrofit Planning	Detailed building data supports better renovation decisions	Construction Industry, Facility Managers	Improving insulation, windows, and overall energy efficiency
Scalability	The method can be applied to large urban areas	Governments, Smart City Developers	City-wide energy analysis and digital twin development

Chapter 8

Takeaways, limitations, and Answers to the research questions

This study represents an important step in the development of Energy Digital Twins (EDTs) by integrating precise rooftop and window identification from 3D point clouds with traditional energy estimations. This chapter presents the scientific conclusions derived from the research findings. Although the research represents progress in EDT development, it possesses certain limitations that have been outlined in this section. The research questions have been concisely addressed at the end of the chapter.

8.1 Scientific Takeaways from this research

The research presented in this study demonstrates the feasibility and limitations of developing Energy Digital Twins (EDTs) using geospatial datasets, particularly aerial photogrammetry-derived point clouds. The integration of geometric reconstruction, machine learning-based feature extraction, and energy simulation provides a comprehensive framework for urban-scale energy analysis. The findings yield several important scientific insights regarding data dependency, feature sensitivity, energy behaviour, and model reliability.

The main message is that the quality of the geometric data, especially the spatial resolution, has a strong influence on the accuracy of the energy modelling. The classification accuracy of KPConv decreases from 80.08% at full resolution (1/1) to 68.20% at 1/16 resolution, a drop of approximately 12 percentage points.

While this reduction is modest it is very uneven in its effects on specific features. The F1-score for rooftop detection is stable ($> 82\%$) even at low resolution, but the F1-score for window detection decreases dramatically, from 78.98 % to 49.10 %. This suggests not all geometric features are equally sensitive to resolution and that window extraction is especially vulnerable because of its small size and complex geometry.

This leads to a second important lesson comprehended from this research which is that the accuracy of EDTs depends strongly on the feature-specific resolution requirements. The results show clearly that resolutions smaller than 1/4 are not appropriate for a reliable window detection. Since the windows are the main source of solar gain and heat loss, errors in the extraction of windows directly propagate into energy simulations. This misclassification can lead to an underestimation of the detected window area, leading to an underestimation of solar gains of several hundred kWh per building per year, for example. This suggests the need for adaptive resolution strategies over uniform down sampling.

A further important finding is the dominance of orientation in solar energy behaviour. Locality 1 has solar gain on the north facing side of 3,200 kWh/year and on the south facing side of 7,800 kWh/year, a difference of 4,600 kWh/year. This confirms that orientation is a key parameter for energy modelling. However, this dependency is not observed in heat loss which is kept relatively constant (7,100-7,300 kWh/year). The asymmetry indicates the direction dependence of the solar gain and the dependence of the heat loss on the thermal transmittance and the temperature gradients. The conductive heat loss is driven by the observed indoor-outdoor temperature difference (ΔT) of about 8 °C for Locality 1 and 9 °C for Locality 2. Even a small increase in ΔT leads to a measurable increase in heat loss, as illustrated by the increase from 7200 kWh/year to 7600 kWh/year between the two localities. This implies that heat loss is mainly controlled by temperature gradients, irrespective of orientation. This research also indicates significant influence of glazing properties, especially the Solar Heat Gain Coefficient (SHGC). The reduction of SHGC from 0.52 (Locality 1) to 0.47 (Locality 2) decreases solar gains from 5,850 kWh/year to 5,200 kWh/year (about 11%). This change increases the net energy deficit from -1,350 kWh/year to -2,400 kWh/year. This result highlights the importance of the correct assignment of material properties in the EDTs, as small perturbations can lead to large differences in the energy results.

Seasonal analysis also exposes the dynamic character of window energy performance. In winter the temperature gradient is very high (up to 16–18°C in Locality 2) and the heat loss is high. There are solar gains, but not enough to compensate these losses. In summer the gradient decreases (3–6°C) reducing heat loss but increasing the effect of solar radiation. This means that the window performance is intrinsically seasonal, and the overall energy balance of the year is the sum of antagonistic effects in the different periods. The comparison between the two locations also shows how sensitive the energy performance is to environmental and contextual factors. Locality 1 has a rather balanced energy profile and Locality 2 is characterised by a strongly loss dominated behaviour. The net energy balance is lower (-1,350 kWh/year against -2,400 kWh/year) because of the combination of lower SHGC, higher heat loss and lower solar gains of Locality 2. This indicates that urban form, climate and material properties jointly affect the energy performance, and that EDTs should consider these factors to achieve trustworthy results. Finally, the validation against EnergyPlus simulations shows that the proposed framework can achieve an acceptable accuracy with an error of +/-5-8% deviation. This confirms that the input of geospatial data and sound assumptions can reproduce realistic energy behaviour at the building scale. But this validation also demonstrates the importance of calibration and the limitations of using only the geometric data.

8.2 Limitations of the work

In spite of the promising results, it is necessary to identify and critically evaluate a number of limitations. These constraints are a result of both the data sources and the modelling approach, and they have implications for the generalisability of the findings as well as their accuracy. Aerial photogrammetry has a number of inherent limitations, one of the most significant of which being its inability to capture facade features. The capacity of aerial imaging to record vertical surfaces with high accuracy is restricted, even though it provides wide coverage. Because of this, the geometry of windows is frequently incomplete or partially obscured, particularly in surroundings that are densely populated. Not only does this have an impact on the precision of window extraction, but it also introduces uncertainty into energy models.

There is also the dependence on the assumed material qualities, which is another constraint. Rather than using the data that was measured, parameters such

as the U-value and the SHGC were allocated based on established ranges. However, even though this method is frequently used in large-scale models, it does increase uncertainty. According to the findings, even minute shifts in solar heat gain coefficient (SHGC) can have a considerable impact on solar gain predictions. This suggests that the absence of direct material data stands as a serious constraint.

The study makes use of static representations of buildings, and it does not take into consideration dynamic elements such as the behaviour of occupants, ventilation, or the operation of shading devices. The existing paradigm does not take into account these elements, despite the fact that they have the potential to considerably impact energy performance. Because of this, the EDT is unable to accurately depict the conditions that exist in the real world. In addition, the environmental circumstances have been simplified, which is another limitation. There are microclimatic changes that are not fully captured by the simulations, despite the fact that climate data were employed. These variations include localized shade, wind effects, and urban heat island phenomena. Despite the fact that these elements are not explicitly modelled, it is possible that they contribute to the disparities that are seen between locations.

Another shortcoming of this research work could be that the framework proposed is dependent on the resolution of the geospatial datasets, primarily on the point cloud density. Although high-resolution data can produce precise analytics and building features, it is possible that such data will not always be accessible for scalable implementations. Maintaining a resolution that is more than $1/4^{\text{th}}$ is required for reliable window identification, which restricts the approach's capacity to scale to a metro scale urban implementation and increases the amount of computing that is required for building feature extraction. A further point to be considered is that the validation against EnergyPlus is based on simplified simulation models and does not include comprehensive calibration with actual measured data. While it is positive that the agreement is within $\pm 5\text{--}8\%$, it is important to note that this does not ensure complete accuracy under all circumstances. It would be necessary to conduct additional rigorous validation using measurements taken in the real world to verify the resilience of the proposed conceptual framework.

The research assumes that the indoor conditions are consistent, with temperatures maintained at approximately 21–22 degrees Celsius throughout the winter and 24–25 degrees Celsius during the summer. Although this assumption

makes modelling simplified and easier, it might not accurately reflect the actual variances in building functioning. This may have an impact on the precision of the estimations regarding heat loss. Based on the outcomes of this study, it is clear that Energy Digital Twins, which are constructed using geospatial datasets, are an effective instrument for doing urban energy analysis. The findings, on the other hand, bring to light the intricacy of the issue as well as the sensitivity of the conclusions to the data and assumptions that were included in the analysis. The identification of the links between resolution, geometry, orientation, material qualities, and energy performance is the most important contribution to the scientific community. Future research should be mainly focused on the inclusion of other data sources such as terrestrial LiDAR and material databases, and on the development of adaptive modelling methodologies dealing with geographical and temporal variability. Overall, the study provides a balanced understanding of the possibilities and the restrictions of using geospatial datasets to create Energy Digital Twins and thus paves the way for further research and practical implementation.

One limitation of the current research is that the dynamic updating and calibration components of the Energy Digital Twin have been defined conceptually but were not implemented and validated using real-time operational data. Future research should focus on integrating smart meters, IoT sensors, weather services, occupancy data, and building management systems to establish automated feedback loops between physical buildings and their digital counterparts. Such integration would enable continuous model calibration, performance monitoring, predictive analytics, and adaptive decision-making, thereby advancing the proposed framework towards a higher level of Digital Twin maturity.

8.3 Brief answers to the research questions

8.3.1 What are the fundamental data resources and their specifications needed to develop a robust and functional Energy Digital Twin for the urban built environments

An Energy Digital Twin (EDT) for urban built environments requires a combination of data resources that can accurately represent energy-relevant building features, particularly windows and roofs. This research demonstrates that

aerial photogrammetry-derived point clouds provide a strong basis for geometric reconstruction, but their reliability is feature-dependent. While rooftops are consistently extracted with high accuracy, window detection is highly sensitive to resolution, with significant degradation observed below a threshold of approximately 1/4 resolution. This establishes a key contribution of the study: data requirements for EDTs are not uniform but feature-specific, with façade elements, especially windows representing the primary source of uncertainty. Semantic datasets generated through deep learning methods such as KPConv neural network for point cloud classification are essential to distinguish roofs, walls, and windows, but their accuracy is directly dependent on the quality of the underlying geometric data.

The study shows that environmental and material data are also important in defining energy performance along with geometry and semantics. Examples of climate data that are required to be locally representative and temporally resolved are temperature and solar radiation. Temperature gradients directly control heat losses and solar radiation governs gains and changes strongly with orientation. At the same time, material properties such as U-values and Solar Heat Gain Coefficient (SHGC) which are not available from geospatial data, have to be sourced from external databases or assumptions. The results highlight the significance of even minor changes in these parameters for energy outcomes, demonstrating a discrepancy between the high precision of geometric data and the uncertainty of material inputs. Moreover, the urban context datasets such as DEM/DSM and the surrounding building geometries are needed for considering the shading and spatial interactions, which affect the solar exposure and the global energy balance. Also the research found the importance of visualisation and integration platforms to make EDTs operational. Multi-source data can be integrated, visualised and analysed at different scales through tools such as ArcGIS Pro GIS software, CesiumJS 3D geospatial platform, MapStore web GIS platform, cloud environments such as Microsoft Azure cloud platform, and real-time visualisation through Unity game engine or Unreal Engine. These platforms not only serve as visualisation tools but also as an essential link between spatial data and simulation outputs, as well as for decision making and scalable EDT deployment. Based on the findings, four major requirements for EDT development are identified:

- **High-resolution geometric data** of built environments capable of capturing façade details, especially windows.

- **Accurate semantic classification** to distinguish energy-relevant building components.
- **Locally representative environmental data** with temporal variability
- **Integrated visualization and data platforms** for analysis, scalability, and practical application

8.3.2 Which building characteristics are essential for energy modelling in an EDT framework and how these characteristics can be systematically extracted from the geospatial datasets?

This research shows that the necessary building characteristics for energy modelling in the context of an Energy Digital Twin (EDT) framework need to be defined not only by their physical relevance but also by their reliability of extraction from airborne point cloud data. The study confirms the importance of parameters such as window geometry, façade area, orientation, tilt and building height. However, it highlights the sensitivity of windows, as errors in their detection directly impact calculations of solar gain and heat loss. At the same time, rooftops are more reliably detected even at lower resolutions. This provides a key contribution: the importance of a building characteristic is dependent on its role in energy modelling and its extractability from data. Furthermore, it is shown that derived indicators such as window to wall ratio (WWR) are highly sensitive to accurate window segmentation and thermal properties (U-value, SHGC) are external inputs that have a significant impact on results.

For this purpose, the research proposes a structured workflow to extract these characteristics from airborne point clouds. The process consists of pre-processing (noise removal, ground filtering), façades detection using geometrical constraints and semantic classification using deep learning methods such as KPConv neural network for point cloud classification. Then, segmentation and planar fitting are used to reconstruct windows and roofs and to compute geometric parameters and derived indicators, like WWR. The results however show that the reliability of extraction is feature dependent and that window detection is significantly degraded at lower resolutions, making it the major bottleneck in EDT development. Table 35 below shows different building characteristics, their role and sources that are important for the development of an EDT for the built environments.

Table 35: Primary building characteristics, their role and sources in EDT development

Characteristic	Role in Energy Modelling	Source / Extraction Method
Rooftop geometry (area, slope)	Solar exposure, heat transfer	Point cloud segmentation
Window area & position	Solar gain, heat loss	Deep learning + segmentation
Façade area	Heat transfer surface	Façade extraction from point clouds
Window-to-Wall Ratio (WWR)	Glazing proportion, energy balance	Derived from window + façade area
Azimuth & tilt	Solar radiation impact	Computed from geometry
Surrounding buildings/shading	Solar obstruction	Point cloud / DSM analysis
U-value	Heat loss through envelope	External datasets / assumptions
SHGC	Solar gain through windows	External datasets / assumptions

8.3.3 How does variation in point cloud density affect the accuracy of extracting building features from point clouds for the purpose of energy modelling?

The density of the point clouds has a direct and significant effect on the accuracy and reliability of the extraction of building features, especially for windows and rooftop features that are important for energy modelling. The results of this study show that the overall classification accuracy decreases from about 80.08% at full resolution (1/1) to 68.20% at 1/16 resolution with a decrease in density, i.e., a decrease of about 12 percentage points. But the reduction is not uniform for windows and rooftop features. Large planar objects such as rooftops are relatively stable, with F1-scores still above 82–87% at 1/16, demonstrating robustness to down sampling. In contrast, small and geometrically complex features such as windows are very sensitive to density variations. Window F1-scores drop from 78.98% at full resolution to 49.10% at 1/16 (Dataset 1) and from 72.10% to 42.00% (Dataset 2), a drop of close to 30 percentage points. This clearly indicates that the window detection does not work at low densities of the point clouds.

This has important consequences for energy modelling, since any error in feature extraction will directly affect derived parameters such as window area, orientation and window-to-wall ratio. For example, under-detecting windows at low densities can cause an underestimation of solar gains of about 500-650 kWh per building per year (based on observed averages, 5,850 kWh/year at full resolution). Misrepresentation of facade geometry also impacts heat loss calculations, which are sensitive to area and temperature gradients. Further results show that the quality of window extraction drops significantly below a resolution of $\sim 1/4$ (window F1 $< \sim 60$ -70%) and it is thus necessary to use at least 1/4 resolution to get reliable window extraction. Thus, while down sampling can reduce computational cost, it results in systematic errors that propagate into energy simulations. This indicates that the point cloud density is an important controlling factor and the need to maintain an adequate resolution for ensuring accurate and reliable Energy Digital Twin outputs.

8.3.4 Which advanced computer vision techniques offer an optimal equilibrium between geometric precision, computational efficiency, and adaptability for extracting architectural elements from point cloud data in the context of EDT development?

The results of this study show that deep learning-based methods especially KPConv is the best method to extract architectural features from point clouds with advanced computer vision techniques in terms of geometrical accuracy, computational efficiency and flexibility. KPConv in full resolution achieves an overall accuracy of ~80.08%, which is better than classical machine learning models such as Random Forest (74.40%) or LightGBM (77.35%). More importantly, for critical features like windows, KPConv obtains an F1-score of 78.98%, compared to 55.61% for Random Forest, indicating its superior capacity to learn detailed geometric features. However, this advantage is compensated for by the larger computational cost. Deep learning models are more expensive to train and require more memory. However, ensemble methods such as XGBoost (accuracy 79.88%) are a good compromise between the high performance of deep learning and lower computational costs making them more suitable for large-scale applications. It is worth mentioning that the density of the point cloud has a big impact on the performance of the model. While KPConv remains quite robust, it drops to 68.20% at 1/16 resolution and window F1-scores fall below 50%, suggesting that even the best models cannot recover from a lack of data quality. In particular, traditional models perform poorly in terms of adaptability, especially for small features such as windows, and degrade faster.

There is no single best approach for all cases. The balance is set by the requirements of the application. The best shot for high resolution high precision EDTs is KPConv. XGBoost or LightGBM are good alternatives for moderate resolutions. So the best approach is not just algorithmic, but data dependent where a balance must be struck between model complexity and input quality so that the feature extraction is reliable for the energy modelling.

References

- Abdessadak, A., Ghennioui, H., Thirion-Moreau, N., Elbhiri, B., Abraim, M., & Merzouk, S. (2025). Digital twin technology and artificial intelligence in energy transition: A comprehensive systematic review of applications. *Energy Reports*, 13, 5196–5218. <https://doi.org/10.1016/j.egyr.2025.04.060>
- Agapaki, E., & Brilakis, I. (2021). CLOI: An Automated Benchmark Framework For Generating Geometric Digital Twins Of Industrial Facilities. *ArXiv Preprint ArXiv:2101.01355*. <https://arxiv.org/abs/2101.01355>
- Aghazadeh Ardebili, A., Zappatore, M., Ramadan, A. I. H. A., Longo, A., & Ficarella, A. (2024). Digital Twins of smart energy systems: a systematic literature review on enablers, design, management and computational challenges. *Energy Informatics*, 7(1), 94. <https://doi.org/10.1186/s42162-024-00385-5>
- Agugiaro, G., Benner, J., Cipriano, P., & Nouvel, R. (2018). The Energy Application Domain Extension for CityGML: enhancing interoperability for urban energy simulations. *Open Geospatial Data, Software and Standards*, 3(1), 2. <https://doi.org/10.1186/s40965-018-0042-y>

- A.H. Selmy, S., E. Kucher, D., Yang, Y., & Jesús García-Navarro, F. (2024). Geospatial Data: Acquisition, Applications, and Challenges. In *Exploring Remote Sensing - Methods and Applications*. IntechOpen. <https://doi.org/10.5772/intechopen.1006635>
- Ahmad Hamdan, Sedat Sonko, Adefunke Fabuyide, Cosmas Dominic Daudu, & Emmanuel Augustine Etukudoh. (2024). Real-time energy monitoring systems: Technological applications in Canada, USA, and Africa. *World Journal of Advanced Research and Reviews*, 21(1), 2053–2063. <https://doi.org/10.30574/wjarr.2024.21.1.0255>
- AlBalkhy, W., Karmaoui, D., Ducoulombier, L., Lafhaj, Z., & Linner, T. (2024). Digital twins in the built environment: Definition, applications, and challenges. *Automation in Construction*, 162, 105368. <https://doi.org/10.1016/j.autcon.2024.105368>
- Albano, R. (2019). Investigation on roof segmentation for 3D building reconstruction from aerial LIDAR point clouds. *Applied Sciences (Switzerland)*, 9(21). <https://doi.org/10.3390/app9214674>
- Alhammad, M., Eames, M., & Vinai, R. (2024). Enhancing Building Energy Efficiency through Building Information Modeling (BIM) and Building Energy Modeling (BEM) Integration: A Systematic Review. *Buildings*, 14(3), 581. <https://doi.org/10.3390/buildings14030581>
- Ali, M. E., Cheema, M. A., Hashem, T., Ulhaq, A., & Babar, M. A. (2024). Enabling Spatial Digital Twins: Technologies, Challenges, and Future Research Directions. *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, 92(6), 761–778. <https://doi.org/10.1007/s41064-024-00301-2>
- Ali, U., Bano, S., Shamsi, M. H., Sood, D., Hoare, C., Zuo, W., Hewitt, N., & O'Donnell, J. (2024). Urban building energy performance prediction and retrofit analysis using data-driven machine learning approach. *Energy and Buildings*, 303, 113768. <https://doi.org/10.1016/j.enbuild.2023.113768>
- Allam, Z., Bibri, S. E., Jones, D. S., Chabaud, D., & Moreno, C. (2022). Unpacking the ‘15-Minute City’ via 6G, IoT, and Digital Twins: Towards a New Narrative for Increasing Urban Efficiency, Resilience, and Sustainability. *Sensors*, 22(4). <https://doi.org/10.3390/s22041369>

- Almadhor, A., Alsubai, S., Kryvinska, N., Ghazouani, N., Bouallegue, B., Al Hejaili, A., & Sampedro, G. A. (2025). A synergistic approach using digital twins and statistical machine learning for intelligent residential energy modelling. *Scientific Reports*, 15(1), 26088. <https://doi.org/10.1038/s41598-025-09760-y>
- Alonso, R., Locci, R., & Reforgiato Recupero, D. (2024). Improving digital twin experience through big data, IoT and social analysis: An architecture and a case study. *Heliyon*, 10(2), e24741. <https://doi.org/10.1016/j.heliyon.2024.e24741>
- Amini, S., Orlich, C., Beil, C., Keler, A., & Bogenberger, K. (2023). *Integrating SUMO in an urban digital twin - a case study from Munich*. <https://doi.org/10.13140/RG.2.2.30752.15364>
- Anselmo, S., & Ferrara, M. (2023). Trends and Evolution of the GIS-Based Photovoltaic Potential Calculation. *Energies*, 16(23). <https://doi.org/10.3390/en16237760>
- Antoniou, V. (2023). On volunteered geographic information quality: a framework for sharing data quality information. In *Geoinformatics for Geosciences* (pp. 149–160). Elsevier. <https://doi.org/10.1016/B978-0-323-98983-1.00009-0>
- Argota Sánchez-Vaquerizo, J. (2025). Urban Digital Twins and metaverses towards city multiplicities: uniting or dividing urban experiences? *Ethics and Information Technology*, 27(1), 4. <https://doi.org/10.1007/s10676-024-09812-3>
- Arowoiya, V. A., Onososen, A. O., Moehler, R. C., & Fang, Y. (2024). Influence of Thermal Comfort on Energy Consumption for Building Occupants: The Current State of the Art. *Buildings*, 14(5), 1310. <https://doi.org/10.3390/buildings14051310>
- Arthur De Jaeger. (2024). *Towards a Right to the Smart City? Citizen Participation in Rotterdam's Urban Digital Twin* . <https://www.centre-for-bold-cities.nl/news/working-paper-14-right-to-the-smart-city-citizen-participation-in-rotterdams-urban-digital>

- Attaran, M., Attaran, S., & Celik, B. G. (2023). The impact of digital twins on the evolution of intelligent manufacturing and Industry 4.0. *Advances in Computational Intelligence*, 3(3), 11. <https://doi.org/10.1007/s43674-023-00058-y>
- Attaran, M., & Celik, B. G. (2023). Digital Twin: Benefits, use cases, challenges, and opportunities. *Decision Analytics Journal*, 6, 100165. <https://doi.org/https://doi.org/10.1016/j.dajour.2023.100165>
- Azrou, M., Guezzaz, A., Zeroual, I., Irshad, A., Mabrouki, J., Benkirane, S., & Chaudhry, S. A. (Eds.). (2024). *Machine Learning, IoT and Artificial Intelligence for Sustainable Development*. MDPI. <https://doi.org/10.3390/books978-3-0365-9925-0>
- Ba, L., Tangour, F., El Abbassi, I., & Absi, R. (2025). Analysis of Digital Twin Applications in Energy Efficiency: A Systematic Review. *Sustainability*, 17(8), 3560. <https://doi.org/10.3390/su17083560>
- Bao, Z., Ng, S. T., Yu, G., Zhang, X., & Ou, Y. (2023). The effect of the built environment on spatial-temporal pattern of traffic congestion in a satellite city in emerging economies. *Developments in the Built Environment*, 14, 100173. <https://doi.org/10.1016/j.dibe.2023.100173>
- Barricelli, B. R., Casiraghi, E., & Fogli, D. (2019). A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications. *IEEE Access*, 7, 167653–167671. <https://doi.org/10.1109/ACCESS.2019.2953499>
- Battye, M. I., & Perinpanayagam, S. (2025). Digital Twins in Fusion Energy Research: Current State and Future Directions. *IEEE Access*, 13, 75787–75821. <https://doi.org/10.1109/ACCESS.2025.3561920>
- Becker, S., & Haala, N. (2009). Grammar Supported Facade Reconstruction from Mobile LIDAR Mapping. In: *Proceedings of the ISPRS Workshop on City Models, Roads and Traffic: CMRT09; Paris, France, September 3-4, 2009*, Pp. 229-234, 38.
- Bera, M., & Nag, P. K. (2025). Energy consumption patterns and efficiency strategies in the built environment: A comprehensive review. *Clean Energy Science and Technology*, 3(4), 400. <https://doi.org/10.18686/cest400>

- Biljecki, F., Ledoux, H., Stoter, J., & Vosselman, G. (2016). The variants of an LOD of a 3D building model and their influence on spatial analyses. *ISPRS Journal of Photogrammetry and Remote Sensing*, 116, 42–54. <https://doi.org/https://doi.org/10.1016/j.isprsjprs.2016.03.003>
- Biljecki, F., & Ohori, K. A. (2015). Automatic semantic-preserving conversion between OBJ and CityGML. *Eurographics Workshop on Urban Data Modelling and Visualisation, UDMV 2015*, 25–30. <https://doi.org/10.2312/udmv.20151345>
- Blasi, S., Ganzaroli, A., & De Noni, I. (2022). Smartening sustainable development in cities: Strengthening the theoretical linkage between smart cities and SDGs. *Sustainable Cities and Society*, 80, 103793. <https://doi.org/https://doi.org/10.1016/j.scs.2022.103793>
- Boccardo, P., La Riccia, L., & Yadav, Y. (2024a). Urban Echoes: Exploring the Dynamic Realities of Cities through Digital Twins. *Land*, 13(5), 635. <https://doi.org/10.3390/land13050635>
- Boccardo, P., La Riccia, L., & Yadav, Y. (2024b). Urban Echoes: Exploring the Dynamic Realities of Cities through Digital Twins. *Land*, 13(5). <https://doi.org/10.3390/land13050635>
- Boltsi, A., Kosmanos, D., Xenakis, A., Chatzimisios, P., & Chaikalis, C. (2025). Towards a Novel Digital Twin Framework Proposal Within the Engineering Design Process for Future Engineers: An IoT Smart Building Use Case. *Sensors*, 25(11), 3504. <https://doi.org/10.3390/s25113504>
- Botín-Sanabria, D. M., Mihaita, A.-S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. de J. (2022). Digital Twin Technology Challenges and Applications: A Comprehensive Review. *Remote Sensing*, 14(6), 1335. <https://doi.org/10.3390/rs14061335>
- Boulch, A., & others. (2020). ConvPoint: Continuous Convolutions. *CVPR*.
- Breiman, L. (2001). Random Forests. *Machine Learning*.
- Buonomano, A., Forzano, C., Giuzio, G. F., Maka, R., Palombo, A., & Russo, G. (2026). Optimising renewable energy community aggregation for urban districts decarbonisation. *Renewable and Sustainable Energy Reviews*, 226, 116411. <https://doi.org/10.1016/j.rser.2025.116411>

- Cao, Y., & Scaioni, M. (2023). A 3D INDOOR-OUTDOOR BENCHMARK DATASET FOR LoD3 BUILDING POINT CLOUD SEMANTIC SEGMENTATION. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-1/W3-2023, 31–37. <https://doi.org/10.5194/isprs-archives-XLVIII-1-W3-2023-31-2023>
- Cárdenas-León, I., Koeva, M., Nourian, P., & Davey, C. (2024). Urban digital twin-based solution using geospatial information for solid waste management. *Sustainable Cities and Society*, 115, 105798. <https://doi.org/https://doi.org/10.1016/j.scs.2024.105798>
- Castellanos, H. G., Aryanfar, Y., Sadabad, A. N., Keçebaş, A., Youssef, M., Akhgarzarandy, F., Farzinfar, M., Ghasemlou, S. M., Ghazy, A., & Kaaniche, K. (2025). Integrating Solar Energy in Urban Development: Strategies for Sustainable and Smart Cities. *International Transactions on Electrical Energy Systems*, 2025(1). <https://doi.org/10.1155/etep/6096036>
- Cavadini, G. B., & Cook, L. M. (2021). Green and cool roof choices integrated into rooftop solar energy modelling. *Applied Energy*, 296, 117082. <https://doi.org/https://doi.org/10.1016/j.apenergy.2021.117082>
- Cespedes-Cubides, A. S., & Jradi, M. (2024). A review of building digital twins to improve energy efficiency in the building operational stage. *Energy Informatics*, 7(1), 11. <https://doi.org/10.1186/s42162-024-00313-7>
- Chair of Geoinformatics Technical University of Munich. (2025). *3D City Database (3DCityDB)*. <https://www.asg.ed.tum.de/en/gis/projects/3dcitydb/>
- Chajaei, F., & Bagheri, H. (2025). LOD1 3D city model from LiDAR: The impact of segmentation accuracy on quality of urban 3D modeling and morphology extraction. *Remote Sensing Applications: Society and Environment*, 38, 101534. <https://doi.org/10.1016/j.rsase.2025.101534>
- Chen, L. (2019). Deep Learning for Building Extraction. *Remote Sensing*.
- Chen, S., Fan, G., & Li, J. (2023). Improving completeness and accuracy of 3D point clouds by using deep learning for applications of digital twins to civil structures. *Advanced Engineering Informatics*, 58, 102196. <https://doi.org/10.1016/j.aei.2023.102196>

- Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.
- Chidiebube Igbokwe, N., Onyeka Nwamekwe, C., Godfrey Ono, C., Celestine Nwabunwanne, E., & Sunday Aguh, P. (2025). The Role of Digital Twins in Optimizing Renewable Energy Utilization and Energy Efficiency in Manufacturing. *Siber International Journal of Digital Business*, 2024(4), 93–111. <https://doi.org/10.38035/sijdb.v1i4>
- Choi, S., & Yoon, S. (2025). AI Agent-Based Intelligent Urban Digital Twin (I-UDT): Concept, Methodology, and Case Studies. *Smart Cities*, 8(1), 28. <https://doi.org/10.3390/smartcities8010028>
- Cina, E., Elbasi, E., Elmazi, G., & AlArnaout, Z. (2025). The Role of AI in Predictive Modelling for Sustainable Urban Development: Challenges and Opportunities. *Sustainability*, 17(11), 5148. <https://doi.org/10.3390/su17115148>
- City of Helsinki. (2025). *Helsinki 3D Mesh Model*. <https://kartta.hel.fi/3d/mesh/>
- Crampen, D., Yadav, Y., Ishar, S., Zlatanova, S., & Tian, W. (2024). Development of 3D UDTs for Traffic Monitoring in Unreal 5 Game Engine. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-4-2024, 131–138. <https://doi.org/10.5194/isprs-archives-XLVIII-4-2024-131-2024>
- Crommelinck, S., Bennett, R., Gerke, M., Nex, F., Yang, M., & Vosselman, G. (2016). Review of Automatic Feature Extraction from High-Resolution Optical Sensor Data for UAV-Based Cadastral Mapping. *Remote Sensing*, 8(8), 689. <https://doi.org/10.3390/rs8080689>
- Cureton, P., & Dunn, N. (2020). Digital twins of cities and evasive futures. In *Shaping Smart for Better Cities: Rethinking and Shaping Relationships between Urban Space and Digital Technologies* (pp. 267–282). Elsevier. <https://doi.org/10.1016/B978-0-12-818636-7.00017-2>
- D’Amico, R. D., Erkoyuncu, J. A., Addepalli, S., & Penver, S. (2022). Cognitive digital twin: An approach to improve the maintenance management. *CIRP*

- Journal of Manufacturing Science and Technology*, 38, 613–630.
<https://doi.org/10.1016/j.cirpj.2022.06.004>
- David, I., Shao, G., Gomes, C., Tilbury, D., & Zarkout, B. (2025). *Interoperability of Digital Twins: Challenges, Success Factors, and Future Research Directions* (pp. 27–46). https://doi.org/10.1007/978-3-031-75390-9_3
- Dawood, N., Dawood, H., Rodriguez-Trejo, S., & Crilly, M. (2017). Visualising urban energy use: the use of LiDAR and remote sensing data in urban energy planning. *Visualization in Engineering*, 5(1), 22.
<https://doi.org/10.1186/s40327-017-0060-3>
- DCS Spatial Services, & NSW Spatial Services. (2024, March). *NSW Spatial Digital Twin*. <https://Nsw.Digitaltwin.Terria.Io/>.
- Delphine Khanna. (2023). *Estimate solar power potential*. ESRI.
<https://learn.arcgis.com/en/projects/estimate-solar-power-potential/>
- Dey, E. K., Awrangjeb, M., Tarsha Kurdi, F., & Stantic, B. (2023). Machine learning-based segmentation of aerial LiDAR point cloud data on building roof. *European Journal of Remote Sensing*, 56(1).
<https://doi.org/10.1080/22797254.2023.2210745>
- Diakite, A. A., Ng, L., Barton, J., Rigby, M., Williams, K., Barr, S., & Zlatanova, S. (2022). Liveable City Digital Twin: A Pilot Project for the City of Liverpool (NSW, AUSTRALIA). *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 10(4/W2-2022), 45–52.
<https://doi.org/10.5194/isprs-annals-X-4-W2-2022-45-2022>
- Diaz-Sarachaga, J. M. (2024). May urban digital twins spur the New Urban Agenda? The Spanish case study. *Sustainable Cities and Society*, 114, 105788. <https://doi.org/10.1016/j.scs.2024.105788>
- Dihan, Md. S., Akash, A. I., Tasneem, Z., Das, P., Das, S. K., Islam, Md. R., Islam, Md. M., Badal, F. R., Ali, Md. F., Ahamed, Md. H., Abhi, S. H., Sarker, S. K., & Hasan, Md. M. (2024). Digital twin: Data exploration, architecture, implementation and future. *Heliyon*, 10(5), e26503.
<https://doi.org/10.1016/j.heliyon.2024.e26503>
- Dong, J. (2020). Random Forest for Urban Mapping. *Remote Sensing*.

- Dritsas, E., & Trigka, M. (2025). Remote Sensing and Geospatial Analysis in the Big Data Era: A Survey. *Remote Sensing*, 17(3), 550. <https://doi.org/10.3390/rs17030550>
- Drive Sweden. (2022). *Stockholm Virtual City*.
- Du, H., Han, Q., & de Vries, B. (2024). *Digital Twin for the Energy Transition in Built Environment: Keyword Co-Occurrence Analysis* (pp. 101–108). https://doi.org/10.1007/978-981-99-8501-2_10
- Du, Y., Sun, T., & Huang, Y. (2024). *A Comprehensive Review of Smart City Initiatives in Singapore Technological Advancements and Urban Planning from 2015 to 2023*. <https://doi.org/10.31219/osf.io/yqfsv>
- Duan, Z., de Wilde, P., Attia, S., & Zuo, J. (2025). Challenges in predicting the impact of climate change on thermal building performance through simulation: A systematic review. *Applied Energy*, 382, 125331. <https://doi.org/10.1016/j.apenergy.2025.125331>
- Ekström, T., Burke, S., Wiktorsson, M., Hassanie, S., Harderup, L.-E., & Arfvidsson, J. (2021). Evaluating the impact of data quality on the accuracy of the predicted energy performance for a fixed building design using probabilistic energy performance simulations and uncertainty analysis. *Energy and Buildings*, 249, 111205. <https://doi.org/10.1016/j.enbuild.2021.111205>
- Eriksson, H., & Harrie, L. (2021). Versioning of 3D city models for municipality applications: Needs, obstacles and recommendations. *ISPRS International Journal of Geo-Information*, 10(2). <https://doi.org/10.3390/ijgi10020055>
- Esri. (2020). *Creating Building Models Using Point Cloud Classification*.
- Ferré-Bigorra, J., Casals, M., & Gangolells, M. (2022). The adoption of urban digital twins. *Cities*, 131. <https://doi.org/10.1016/j.cities.2022.103905>
- Francisco, A., Mohammadi, N., & Taylor, J. E. (2020). Smart City Digital Twin–Enabled Energy Management: Toward Real-Time Urban Building Energy Benchmarking. *Journal of Management in Engineering*, 36(2). [https://doi.org/10.1061/\(asce\)me.1943-5479.0000741](https://doi.org/10.1061/(asce)me.1943-5479.0000741)

- FrontierSI, AURIN, UNSW Research Infrastructure, NSW Spatial Services, Data61, QLD DNRME, & Astrolabe. (2022, June). *Liveable city digital twin: Analytics for Agile decision making*. <https://Lcdt-Project.Unsw.Edu.Au/>.
- Gemeente Rotterdam. (2024). *3D Rotterdam*. <https://www.3drotterdam.nl/>
- GitHub. (2019). *XGBoost Classification with Python and Scikit-Learn*.
- GitHub. (2023). *LightGBM Classification Project Notebook*.
- Grilli, E. (2017). Point Cloud Classification. *Remote Sensing*.
- Guo, Y. (2020). Deep Learning for 3D Point Clouds Survey. *IEEE TPAMI*.
- Guo, Y., Wang, H., Hu, Q., Liu, H., Liu, L., & Bennamoun, M. (2021). Deep Learning for 3D Point Clouds: A Survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 43(12), 4338–4364. <https://doi.org/10.1109/TPAMI.2020.3005434>
- Hakim, Y. F., & Tsai, F. (2026). Building Footprint Extraction for Large-Scale Basemaps Using Very-High-Resolution Satellite Imagery. *Buildings*, 16(3), 675. <https://doi.org/10.3390/buildings16030675>
- Hämäläinen, M. (2021). Urban development with dynamic digital twins in Helsinki city. *IET Smart Cities*, 3(4), 201–210. <https://doi.org/10.1049/smc2.12015>
- Hananto, A. L., Tirta, A., Herawan, S. G., Idris, M., Soudagar, M. E. M., Djamari, D. W., & Veza, I. (2024). Digital Twin and 3D Digital Twin: Concepts, Applications, and Challenges in Industry 4.0 for Digital Twin. *Computers*, 13(4), 100. <https://doi.org/10.3390/computers13040100>
- Hernández-Herráez, G., Velaz-Acera, N., Del Pozo, S., & Lagüela, S. (2025). The Role of Geospatial Techniques for Renewable Hydrogen Value Chain: A Systematic Review of Current Status, Challenges and Future Developments. *Applied Sciences*, 15(16), 8777. <https://doi.org/10.3390/app15168777>
- Hossain, M. I., Ferdous, M. N., Suvo, S. S., & Hossan, M. R. (2025). Spatiotemporal analysis of vegetation influence on land surface temperature and urban heat Island using a digital twin framework. *Discover Cities*, 2(1), 125. <https://doi.org/10.1007/s44327-025-00175-y>

- Hu, M., Liu, Z., Huang, Y., Wei, M., & Yuan, B. (2023). Estimation of Rooftop Solar Photovoltaic Potential Based on High-Resolution Images and Digital Surface Models. *Buildings*, 13(11), 2686. <https://doi.org/10.3390/buildings13112686>
- Huang, X., Liu, Y., Huang, L., Onstein, E., & Merschbrock, C. (2023). BIM and IoT data fusion: The data process model perspective. *Automation in Construction*, 149, 104792. <https://doi.org/10.1016/j.autcon.2023.104792>
- Hussein, N. A.-H. K., & Basel, O. M. (2024). Integrating Renewable Energy Systems into Urban Planning for Sustainable Cities. *ESTIDAMAA*, 2024, 15–21. <https://doi.org/10.70470/ESTIDAMAA/2024/003>
- Hyre, A., Harris, G., Osho, J., Pantelidakis, M., Mykoniatis, K., & Liu, J. (2022). Digital twins: Representation, Replication, Reality, and Relational (4Rs). *Manufacturing Letters*, 31, 20–23. <https://doi.org/10.1016/J.MFGLET.2021.12.004>
- Iossa, R., Domenighini, P., & Cotana, F. (2025). Digital Twins from Building to Urban Areas: An Open Opportunity to Energy, Environmental, Economic and Social Benefits. *Applied Sciences*, 15(19), 10795. <https://doi.org/10.3390/app151910795>
- ISO/TC 211. (2020). *Geographic information — Metadata (ISO Standard No. 19115:2020)*. <https://www.iso.org/standard/67253.html>
- Jamil, M. R. (2025). Integrated Approaches to Urban Energy Efficiency and Carbon Sequestration: A Framework for Implementing Urban Digital Twins. *Smart Design Policies*, 2(1), 73–91. <https://doi.org/10.38027/smart.v2n1-5>
- Javed, A. R., Shahzad, F., ur Rehman, S., Zikria, Y. Bin, Razzak, I., Jalil, Z., & Xu, G. (2022). Future smart cities: requirements, emerging technologies, applications, challenges, and future aspects. *Cities*, 129, 103794. <https://doi.org/https://doi.org/10.1016/j.cities.2022.103794>
- Jeddoub, I., & others. (2023). Digital Twins for cities: Analyzing the gap between theoretical definitions and implementations. *Sustainable Cities and Society*.
- Jeddoub, I., Roquet, M., Oudadda, Y., Hajji, R., Dewallef, P., & Billen, R. (2025). A Lightweight Framework for Seamless Integration of Building Energy Simulations into Urban Digital Twins. *The International Archives of the*

- Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII-4/W15-2025*, 77–84. <https://doi.org/10.5194/isprs-archives-XLVIII-4-W15-2025-77-2025>
- JG Times. (2026). *Japan's Point Cloud Data and Digital Twin Initiatives*.
- Jovanović, D., Milovanov, S., Ruskovski, I., Govedarica, M., Sladić, D., Radulović, A., & Pajić, V. (2020). Building Virtual 3D City Model for Smart Cities Applications: A Case Study on Campus Area of the University of Novi Sad. *ISPRS International Journal of Geo-Information*, 9(8), 476. <https://doi.org/10.3390/ijgi9080476>
- Kaiser, J., & Dedić, M. (2024). Influence of Material on the Density of a Point Cloud Created Using a Structured-Light 3D Scanner. *Applied Sciences*, 14(4), 1476. <https://doi.org/10.3390/app14041476>
- Kandelan, S. N., Mohammed, N. A. C., Grewal, K. S., Farooque, A. A., & Hu, Y. (2024). Geometric data in urban building energy modeling: Current practices and the case for automation. *Journal of Building Engineering*, 97, 110836. <https://doi.org/10.1016/j.jobbe.2024.110836>
- Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2026). *LightGBM: A Highly Efficient Gradient Boosting Framework*.
- Keirstead, J., Jennings, M., & Sivakumar, A. (2012). A review of urban energy system models: Approaches, challenges and opportunities. *Renewable and Sustainable Energy Reviews*, 16(6), 3847–3866. <https://doi.org/10.1016/j.rser.2012.02.047>
- Ketzler, B., Naserentin, V., Latino, F., Zangelidis, C., Thuvander, L., & Logg, A. (2020). Digital Twins for Cities: A State of the Art Review. *Built Environment*, 46(4), 547–573. <https://doi.org/10.2148/benv.46.4.547>
- Kochanek, A., Generowicz, A., & Załona, T. (2025). The Role of Geographic Information Systems in Environmental Management and the Development of Renewable Energy Sources—A Review Approach. *Energies*, 18(17), 4740. <https://doi.org/10.3390/en18174740>
- Kohler, J. C., Lyons, P., Hart, R. G., & Curcija, D. C. (2019). *A Comparison Of The Latest Window Modeling Methods In EnergyPlus*. 4902–4909. <https://doi.org/10.26868/25222708.2019.210908>

- Koirala, B., Bendiek-Laranjo, A., Biéron, M., Chen, Y. C., Humbert, G., Hunhevicz, J., Mutschler, R., Obrist, M., Romano, E., Vulic, N., Yazdanie, M., & Mavromatidis, G. (2025). Ten questions concerning the design of urban energy systems. *Building and Environment*, 283, 113348. <https://doi.org/10.1016/j.buildenv.2025.113348>
- Koirala, B., Cai, H., Khayatian, F., Munoz, E., An, J. G., Mutschler, R., Sulzer, M., De Wolf, C., & Orehounig, K. (2024a). Digitalization of urban multi-energy systems – Advances in digital twin applications across life-cycle phases. *Advances in Applied Energy*, 16, 100196. <https://doi.org/10.1016/j.adapen.2024.100196>
- Koirala, B., Cai, H., Khayatian, F., Munoz, E., An, J. G., Mutschler, R., Sulzer, M., De Wolf, C., & Orehounig, K. (2024b). Digitalization of urban multi-energy systems – Advances in digital twin applications across life-cycle phases. *Advances in Applied Energy*, 16, 100196. <https://doi.org/10.1016/j.adapen.2024.100196>
- Koldasbayeva, D., Tregubova, P., Gasanov, M., Zaytsev, A., Petrovskaia, A., & Burnaev, E. (2024a). Challenges in data-driven geospatial modeling for environmental research and practice. *Nature Communications*, 15(1), 10700. <https://doi.org/10.1038/s41467-024-55240-8>
- Koldasbayeva, D., Tregubova, P., Gasanov, M., Zaytsev, A., Petrovskaia, A., & Burnaev, E. (2024b). Challenges in data-driven geospatial modeling for environmental research and practice. *Nature Communications*, 15(1), 10700. <https://doi.org/10.1038/s41467-024-55240-8>
- Kumari, N., & others. (2023). A Comprehensive Review of Digital Twin Technology for Grid-Connected Microgrid Systems. *Energies*.
- Labetski, A., Vitalis, S., Biljecki, F., Arroyo Ohori, K., & Stoter, J. (2023). 3D building metrics for urban morphology. *International Journal of Geographical Information Science*, 37(1), 36–67. <https://doi.org/10.1080/13658816.2022.2103818>
- Lafarge, F., & Mallet, C. (2012). Creating Large-Scale City Models from 3D-Point Clouds: A Robust Approach with Hybrid Representation. *International Journal of Computer Vision*, 99(1), 69–85. <https://doi.org/10.1007/s11263-012-0517-8>

- Lam, P.-D., Gu, B.-H., Lam, H.-K., Ok, S.-Y., & Lee, S.-H. (2024). Digital Twin Smart City: Integrating IFC and CityGML with Semantic Graph for Advanced 3D City Model Visualization. *Sensors*, 24(12), 3761. <https://doi.org/10.3390/s24123761>
- Leica Geosystems AG. (2025). *Leica CityMapper-2 High-Performance Urban Mapping Sensor*. <https://leica-geosystems.com/products/airborne-systems/hybrid-sensors/leica-citymapper-2>
- Li, H., & Hong, T. (2025). A digital twin platform for building performance monitoring and optimization: Performance simulation and case studies. *Building Simulation*, 18(6), 1561–1579. <https://doi.org/10.1007/s12273-025-1290-2>
- Li, Y., & Feng, H. (2025a). How geospatial technologies are transforming urban net-zero energy buildings: A comprehensive review of insights, challenges, and future directions. *Journal of Building Engineering*, 104, 112357. <https://doi.org/10.1016/j.jobbe.2025.112357>
- Li, Y., & Feng, H. (2025b). Integrating urban building energy modeling (UBEM) and urban-building environmental impact assessment (UB-EIA) for sustainable urban development: A comprehensive review. *Renewable and Sustainable Energy Reviews*, 213, 115471. <https://doi.org/10.1016/j.rser.2025.115471>
- Liu, C., & Tian, Y. (2023). Recognition of digital twin city from the perspective of complex system theory: Lessons from Chinese practice. *Journal of Urban Management*, 12(2), 182–192. <https://doi.org/10.1016/j.jum.2023.04.001>
- Liu, H., Liang, J., Liu, Y., & Wu, H. (2023). A Review of Data-Driven Building Energy Prediction. *Buildings*, 13(2), 532. <https://doi.org/10.3390/buildings13020532>
- Liu, X., Wang, X., Wright, G., Cheng, J., Li, X., & Liu, R. (2017). A State-of-the-Art Review on the Integration of Building Information Modeling (BIM) and Geographic Information System (GIS). *ISPRS International Journal of Geo-Information*, 6(2), 53. <https://doi.org/10.3390/ijgi6020053>
- Lopez-Cabeza, V. P., Videras-Rodriguez, M., & Gomez-Melgar, S. (2025). An Open-Source Urban Digital Twin for Enhancing Outdoor Thermal Comfort

- in the City of Huelva (Spain). *Smart Cities*, 8(5), 160.
<https://doi.org/10.3390/smartcities8050160>
- Lucchi, E., Polo Lopez, C. S., & Franco, G. (2020). A conceptual framework on the integration of solar energy systems in heritage sites and buildings. *IOP Conference Series: Materials Science and Engineering*, 949(1), 012113.
<https://doi.org/10.1088/1757-899X/949/1/012113>
- Luigi La Riccia, Vittorio Scolamiero, Yogender Yadav, & Allegra Eusebio. (2024). Turin digital twins: initiatives and challenges. *“Earth Observation: Current Challenges and Opportunities for Environmental Monitoring.”*
- Lyons, P., Wong, J., & Bhandari, M. (2010). *A COMPARISON OF WINDOW MODELING METHODS IN ENERGYPLUS 4.0*.
- Mahjoobi, E., & Rafiei, F. (2024). Exploring the Potential of Geospatial Data: An In-Depth Investigation. In *Exploring Remote Sensing - Methods and Applications*. IntechOpen. <https://doi.org/10.5772/intechopen.1006999>
- Mahmoud, A. (2022). The Influence of Buildings Proportions and Orientations on Energy Demand for Cooling in Hot Arid Climate. *SVU-International Journal of Engineering Sciences and Applications*, 3(1), 8–20.
<https://doi.org/10.21608/svusrc.2022.119125.1028>
- Maiullari, D., Nageli, C., Rudena, A., & Thuvander, L. (2023). Gothenburg Digital Twin. Modelling and communicating the effect of temperature change scenarios on building demand. *Journal of Physics: Conference Series*, 2600(3), 032006. <https://doi.org/10.1088/1742-6596/2600/3/032006>
- Majidi Nezhad, M., Moradian, S., Guezgouz, M., Shi, X., Avelin, A., & Wallin, F. (2025). A GIS-portal platform from the data perspective to energy hub digitalization solutions- A review and a case study. *Renewable and Sustainable Energy Reviews*, 223, 116019.
<https://doi.org/10.1016/j.rser.2025.116019>
- Mallet, C., & Raimond, A.-M. (2026). *The Global-Local loop: what is missing in bridging the gap between geospatial data from numerous communities?* <http://arxiv.org/abs/2603.20305>
- Maru, M. B., Wang, Y., Kim, H., Yoon, H., & Park, S. (2023). Improved building facade segmentation through digital twin-enabled RandLA-Net with

- empirical intensity correction model. *Journal of Building Engineering*, 78, 107520. <https://doi.org/10.1016/j.jobbe.2023.107520>
- Mbasso, W. F., Harrison, A., Dagal, I., Jangir, P., Khishe, M., Kotb, H., Shaikh, M. S., Smerat, A., Fendzi Donfack, E., & Kumar, R. (2025a). Digital twins in renewable energy systems: A comprehensive review of concepts, applications, and future directions. *Energy Strategy Reviews*, 61, 101814. <https://doi.org/10.1016/j.esr.2025.101814>
- Mbasso, W. F., Harrison, A., Dagal, I., Jangir, P., Khishe, M., Kotb, H., Shaikh, M. S., Smerat, A., Fendzi Donfack, E., & Kumar, R. (2025b). Digital twins in renewable energy systems: A comprehensive review of concepts, applications, and future directions. *Energy Strategy Reviews*, 61, 101814. <https://doi.org/10.1016/j.esr.2025.101814>
- Meng, S., Wu, L., Li, M., Yeh, A. G. O., & Xue, F. (2026). Automated window detection for digital twin buildings: A generalized ‘sandwich’ model and practical guidelines. *Energy and Buildings*, 360, 117384. <https://doi.org/10.1016/j.enbuild.2026.117384>
- Middelhaue, L., Girardin, L., Baldi, F., & Maréchal, F. (2021). Potential of Photovoltaic Panels on Building Envelopes for Decentralized District Energy Systems. *Frontiers in Energy Research*, 9. <https://doi.org/10.3389/fenrg.2021.689781>
- MLIT Japan. (2025). *Plateau View 4.0*. <https://plateauview.mlit.go.jp/>
- Mydlarz, C., Sharma, M., Lockerman, Y., Steers, B., Silva, C., & Bello, J. P. (2019). The Life of a New York City Noise Sensor Network. *Sensors*, 19(6), 1415. <https://doi.org/10.3390/s19061415>
- Mylonas, G., Kalogeras, A., Kalogeras, G., Anagnostopoulos, C., Alexakos, C., & Munoz, L. (2021). Digital Twins From Smart Manufacturing to Smart Cities: A Survey. *IEEE Access*, 9, 143222–143249. <https://doi.org/10.1109/ACCESS.2021.3120843>
- Najjar, M., Indraganti, M., & Furlan, R. (2025). The Role of Building Geometry in Urban Heat Islands: Case of Doha, Qatar. *Designs*, 9(3), 77. <https://doi.org/10.3390/designs9030077>

- Naserentin, V., & Logg, A. (2022). Digital twins for city simulation: Automatic, efficient, and robust mesh generation. *ArXiv Preprint ArXiv:2210.05250*. <https://arxiv.org/abs/2210.05250>
- Nielsen, C. P., da Silva, E. R., & Yu, F. (2020). Digital Twins and Blockchain – Proof of Concept. *Procedia CIRP*, 93, 251–255. <https://doi.org/10.1016/j.procir.2020.04.104>
- Nouvel, R., Zirak, M., Coors, V., & Eicker, U. (2017). The influence of data quality on urban heating demand modeling using 3D city models. *Computers, Environment and Urban Systems*, 64, 68–80. <https://doi.org/10.1016/j.compenvurbsys.2016.12.005>
- Nowacka, A., & Remondino, F. (2018). GEOSPATIAL DATA FOR ENERGY EFFICIENCY AND LOW CARBON CITIES – OVERVIEW, EXPERIENCES AND NEW PERSPECTIVES –. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-4, 467–474. <https://doi.org/10.5194/isprs-archives-XLII-4-467-2018>
- O'Dwyer, E., Pan, I., Charlesworth, R., Butler, S., & Shah, N. (2020). Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. *Sustainable Cities and Society*, 62. <https://doi.org/10.1016/j.scs.2020.102412>
- Omran, H., Mehdipour, A., Oteng, D., & Al-Obaidi, K. M. (2025). The uptake of urban digital twins in the built environment: a pathway to resilient and sustainable cities. *Computational Urban Science*, 5(1), 20. <https://doi.org/10.1007/s43762-025-00177-x>
- Onma Enyejo, J., Peter Fajana, O., Sele Jok, I., Judith Ihejirika, C., Olusola Awotiwon, B., & Motilola Olola, T. (2024). Digital Twin Technology, Predictive Analytics, and Sustainable Project Management in Global Supply Chains for Risk Mitigation, Optimization, and Carbon Footprint Reduction through Green Initiatives. *International Journal of Innovative Science and Research Technology (IJISRT)*, 609–630. <https://doi.org/10.38124/ijisrt/IJISRT24NOV1344>
- Oraiopoulos, A., & Howard, B. (2022). On the accuracy of Urban Building Energy Modelling. *Renewable and Sustainable Energy Reviews*, 158, 111976. <https://doi.org/10.1016/j.rser.2021.111976>

- Osadcha, I., Jurelionis, A., & Fokaides, P. (2023). Geometric parameter updating in digital twin of built assets: A systematic literature review. *Journal of Building Engineering*, 73, 106704. <https://doi.org/10.1016/j.jobbe.2023.106704>
- Padsala, R., Falay, B., Hainoun, A., & Coors, V. (2025). A Data-Driven Urban Digital Twin Approach for Evaluating Positive Energy District Potential Using OGC Standards in Stuttgart. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-4/W16-2025, 67–74. <https://doi.org/10.5194/isprs-archives-XLVIII-4-W16-2025-67-2025>
- Pan, Y., Zhu, M., Lv, Y., Yang, Y., Liang, Y., Yin, R., Yang, Y., Jia, X., Wang, X., Zeng, F., Huang, S., Hou, D., Xu, L., Yin, R., & Yuan, X. (2023). Building energy simulation and its application for building performance optimization: A review of methods, tools, and case studies. *Advances in Applied Energy*, 10, 100135. <https://doi.org/10.1016/j.adapen.2023.100135>
- Parida, B., Iniyan, S., & Goic, R. (2011). A review of solar photovoltaic technologies. *Renewable and Sustainable Energy Reviews*, 15(3), 1625–1636. <https://doi.org/10.1016/j.rser.2010.11.032>
- Peldon, D., Banihashemi, S., LeNguyen, K., & Derrible, S. (2024a). Navigating urban complexity: The transformative role of digital twins in smart city development. *Sustainable Cities and Society*, 111, 105583. <https://doi.org/10.1016/j.scs.2024.105583>
- Peldon, D., Banihashemi, S., LeNguyen, K., & Derrible, S. (2024b). Navigating urban complexity: The transformative role of digital twins in smart city development. *Sustainable Cities and Society*, 111, 105583. <https://doi.org/10.1016/j.scs.2024.105583>
- Philibert Petit, E. (2022). Smart City Technologies plus Nature-Based Solutions: viable and valuable resources for urban resilience. In *Smart Cities Policies and Financing* (pp. 377–398). Elsevier. <https://doi.org/10.1016/B978-0-12-819130-9.00001-2>
- Prasanth, A., Sharma, V., Dhanaraj, R. K., & Raj, P. (2025). *Blockchain-Based Digital Twins*. Apple Academic Press. <https://doi.org/10.1201/9781003569046>

- Pu, S., & Vosselman, G. (2009). Building Facade Reconstruction by Fusing Terrestrial Laser Points and Images. *Sensors*, 9(6), 4525–4542. <https://doi.org/10.3390/s90604525>
- Qi, C. (2017). PointNet: Deep Learning on Point Sets. *CVPR*.
- Quek, H. Y., Sielker, F., Akroyd, J., Bhawe, A. N., von Richthofen, A., Herthogs, P., Yamu, C. van der L., Wan, L., Nohta, T., Burgess, G., Lim, M. Q., Mosbach, S., & Kraft, M. (2023). The conundrum in smart city governance: Interoperability and compatibility in an ever-growing ecosystem of digital twins. *Data & Policy*, 5, e6. <https://doi.org/10.1017/dap.2023.1>
- Rahmati, B., Rabiei-Dastjerdi, H., Bibri, S. E., Aghajani, M. A., & Kazemi, M. (2024). Reducing urban energy consumption and carbon emissions: a novel GIS-based model for sustainable spatial accessibility to local services and resources. *Computational Urban Science*, 4(1), 37. <https://doi.org/10.1007/s43762-024-00139-9>
- Ramani, V., Ignatius, M., Lim, J., Biljecki, F., & Miller, C. (2023). A Dynamic Urban Digital Twin Integrating Longitudinal Thermal Imagery for Microclimate Studies. *Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, 421–428. <https://doi.org/10.1145/3600100.3626345>
- Ramirez Camargo, L., & Stoglehner, G. (2018). Spatiotemporal modelling for integrated spatial and energy planning. *Energy, Sustainability and Society*, 8(1), 32. <https://doi.org/10.1186/s13705-018-0174-z>
- Rao, C. K., Sahoo, S. K., & Yanine, F. F. (2025). A comprehensive review of smart energy management systems for photovoltaic power generation utilizing the internet of things. *Unconventional Resources*, 7, 100197. <https://doi.org/10.1016/j.uncres.2025.100197>
- Rayegan, S., Katal, A., Wang, L. (Leon), Zmeureanu, R., Eicker, U., Mortezaazadeh, M., & Tahmasebi, S. (2024). Modeling building energy self-sufficiency of using rooftop photovoltaics on an urban scale. *Energy and Buildings*, 324, 114863. <https://doi.org/10.1016/j.enbuild.2024.114863>
- REINHART, C., DOGAN, T., JAKUBIEC, A., RAKHA, T., & SANG, A. (2013, August 28). *Umi – An Urban Simulation Environment For Building Energy*

- Use, Daylighting And Walkability.*
<https://doi.org/10.26868/25222708.2013.1404>
- Ren, Y., Li, X., Jin, F., Li, C., Liu, W., Li, E., & Zhang, L. (2024). Extracting Regular Building Footprints Using Projection Histogram Method from UAV-Based 3D Models. *ISPRS International Journal of Geo-Information*, 14(1), 6. <https://doi.org/10.3390/ijgi14010006>
- Richiardi, C., Caroscio, L., Crescini, E., De Marchi, M., De Pieri, G. M., Ceresi, C., Baldo, F., Francobaldi, M., & Pappalardo, S. E. (2025). A global downstream approach to mapping surface urban heat islands using open data and collaborative technology. *Sustainable Geosciences: People, Planet and Prosperity*, 1, 100006. <https://doi.org/10.1016/j.susgeo.2025.100006>
- Rojas-Colmenares, L. S., Rizo-Maestre, C., Gómez-Donoso, F., & Saura-Gómez, P. (2025). Interactive Digital Twin Workflow for Energy Assessment of Buildings: Integration of Photogrammetry, BIM and Thermography. *Applied Sciences*, 15(23), 12599. <https://doi.org/10.3390/app152312599>
- Roman, O., Bassier, M., Agugiaro, G., Arroyo Otori, K., Farella, E. M., & Remondino, F. (2025). Scan-to-EDTs: Automated Generation of Energy Digital Twins from 3D Point Clouds. *Buildings*, 15(22), 4060. <https://doi.org/10.3390/buildings15224060>
- Romero Rodríguez, L., Duminil, E., Sánchez Ramos, J., & Eicker, U. (2017). Assessment of the photovoltaic potential at urban level based on 3D city models: A case study and new methodological approach. *Solar Energy*, 146, 264–275. <https://doi.org/10.1016/j.solener.2017.02.043>
- Roney Bernardes, E. (2024). Advantages and Challenges of Using Renewable Sources with Smart Meters for Better Energy Efficiency-Use Case of a Brazilian Rural Area. In *ICT for Smart Grid - Recent Advances, New Perspectives, and Applications*. IntechOpen. <https://doi.org/10.5772/intechopen.1004442>
- Saeed, Z. O., Mancini, F., Glusac, T., & Izadpanahi, P. (2022). Future City, Digital Twinning and the Urban Realm: A Systematic Literature Review. In *Buildings* (Vol. 12, Number 5). MDPI. <https://doi.org/10.3390/buildings12050685>

- Sáenz de Tejada, C., Daher, C., Hidalgo, L., Netanyahu, S., Nieuwenhuijsen, M., & Braubach, M. (2024). Urban planning, design and management approaches to building urban resilience: a rapid review of the evidence. *Cities & Health*, 8(5), 932–955. <https://doi.org/10.1080/23748834.2024.2364491>
- Sakti, A. D., Rohayani, P., Izzah, N. A., Toya, N. A., Hadi, P. O., Octavianti, T., Harjupa, W., Caraka, R. E., Kim, Y., Avtar, R., Puttanapong, N., Lin, C.-H., & Wikantika, K. (2023). Spatial integration framework of solar, wind, and hydropower energy potential in Southeast Asia. *Scientific Reports*, 13(1), 340. <https://doi.org/10.1038/s41598-022-25570-y>
- Schrotter, G., & Hürzeler, C. (2020). The Digital Twin of the City of Zurich for Urban Planning. *PFG - Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, 88(1), 99–112. <https://doi.org/10.1007/s41064-020-00092-2>
- Semanjski, I. C. (2023). Digital twin. In *Smart Urban Mobility* (pp. 223–238). Elsevier. <https://doi.org/10.1016/B978-0-12-820717-8.00007-5>
- Seoul Metropolitan Government. (2026). *Spatial Data for Smart City Seoul*.
- Sharifi, A., Allam, Z., Bibri, S. E., & Khavarian-Garmsir, A. R. (2024). Smart cities and sustainable development goals (SDGs): A systematic literature review of co-benefits and trade-offs. *Cities*, 146, 104659. <https://doi.org/https://doi.org/10.1016/j.cities.2023.104659>
- Sharma, N. (2025). *Digital Twin Foundations (Part 1): Where Cities Learn, Think, & Evolve*.
- Sharma, S. K., Mohapatra, S., Sharma, R. C., Alturjman, S., Altrjman, C., Mostarda, L., & Stephan, T. (2022). Retrofitting Existing Buildings to Improve Energy Performance. *Sustainability*, 14(2), 666. <https://doi.org/10.3390/su14020666>
- Shi, C., Huang, M., Su, S., Hu, Q., Wang, W., & Li, X. (2025). Energy-resilient performance-based generative design to adapt to future climate change using urban building energy model: A case study of residential block design. *Sustainable Cities and Society*, 131, 106769. <https://doi.org/10.1016/j.scs.2025.106769>

- Simio Staff. (2025, May). *Digital Twin Evolution: A 30-Year Journey That Changed Industry*. <https://www.simio.com/digital-twin-evolution-a-30-year-journey-that-changed-industry/>
- Sisman, S., Kara, A., & Aydinoglu, A. C. (2025). Leveraging spatial data infrastructure for machine learning based building energy performance prediction. *PLOS One*, 20(10), e0335531. <https://doi.org/10.1371/journal.pone.0335531>
- Soergel, B., Kriegler, E., Weindl, I., Rauner, S., Dirnaichner, A., Ruhe, C., Hofmann, M., Bauer, N., Bertram, C., Bodirsky, B. L., Leimbach, M., Leininger, J., Levesque, A., Luderer, G., Pehl, M., Wingers, C., Baumstark, L., Beier, F., Dietrich, J. P., ... Popp, A. (2021). A sustainable development pathway for climate action within the UN 2030 Agenda. *Nature Climate Change*, 11(8), 656–664. <https://doi.org/10.1038/s41558-021-01098-3>
- Sola, A., Corchero, C., Salom, J., & Sanmarti, M. (2020). Multi-domain urban-scale energy modelling tools: A review. *Sustainable Cities and Society*, 54, 101872. <https://doi.org/10.1016/j.scs.2019.101872>
- Somanath, S., Naserentin, V., Eleftheriou, O., Sjölie, D., Wästberg, B. S., & Logg, A. (2024). Towards Urban Digital Twins: A Workflow for Procedural Visualization Using Geospatial Data. *Remote Sensing*, 16(11), 1939. <https://doi.org/10.3390/rs16111939>
- Son, T. H., Weedon, Z., Yigitcanlar, T., Sanchez, T., Corchado, J. M., & Mehmood, R. (2023). Algorithmic urban planning for smart and sustainable development: Systematic review of the literature. *Sustainable Cities and Society*, 94, 104562. <https://doi.org/10.1016/j.scs.2023.104562>
- SPARC Faculty. (2023). *Digital Twins in Geospatial Research: SPARC Digital Twins Workshop Final Report*.
- Subramanian, N., & Stonier, A. A. (2026). Digital twin applications and case studies in modern power grid management. *Energy Reports*, 15, 109218. <https://doi.org/10.1016/j.egyr.2026.109218>
- Sun, X. (2021). Machine Learning for LiDAR Classification. *ISPRS*.
- Thomas, H. (2019). *KPConv: Kernel Point Convolutions*.

- Thomas, H., & others. (2019). KPConv: Flexible and Deformable Convolution for Point Clouds. *ICCV*.
- Tiwari, A., Meir, I. A., & Karnieli, A. (2020). Object-based image procedures for assessing the solar energy photovoltaic potential of heterogeneous rooftops using airborne LiDAR and orthophoto. *Remote Sensing*, 12(2). <https://doi.org/10.3390/rs12020223>
- Tokyo Metropolitan Government Digital Twin Project. (2024). *Roadmap for Applications of Digital Twin Technology as a Social Infrastructure*. https://info.tokyo-digitaltwin.metro.tokyo.lg.jp/docs/roadmap/roadmap_docs_en.pdf
- United Nations. (2023). *The-Sustainable-Development-Goals-Report-2023: Towards a Rescue Plan for People and Planet*. <https://unstats.un.org/sdgs/report/2023/>
- Venkateswarlu, N., & Sathiyamoorthy, M. (2025). Sustainable innovations in digital twin technology: a systematic review about energy efficiency and indoor environment quality in built environment. *Frontiers in Built Environment*, 11. <https://doi.org/10.3389/fbuil.2025.1523464>
- Verma, P., Kumari, T., & Raghubanshi, A. S. (2021). Energy emissions, consumption and impact of urban households: A review. *Renewable and Sustainable Energy Reviews*, 147, 111210. <https://doi.org/https://doi.org/10.1016/j.rser.2021.111210>
- Villani, L., Gugliermetti, L., Barucco, M. A., & Cinquepalmi, F. (2025). A Digital Twin Framework to Improve Urban Sustainability and Resiliency: The Case Study of Venice. *Land*, 14(1), 83. <https://doi.org/10.3390/land14010083>
- Volk, R., Stengel, J., & Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings — Literature review and future needs. *Automation in Construction*, 38, 109–127. <https://doi.org/https://doi.org/10.1016/j.autcon.2013.10.023>
- VU.CITY. (2026). *London 3D Model and Digital Twin*.
- Wang, N., Cheng, R., Chen, J., & Zhang, M. (2024). Streamlining BIM models for GIS integration: an advanced approach to building envelope extraction.

- International Journal of Digital Earth*, 17(1).
<https://doi.org/10.1080/17538947.2024.2368708>
- Wang, S., Tian, C., Zhou, C., Wu, Y., Ametefe, D. S., John, D., & Ametefe, M. A. (2026). The Role of Digital Twin Technology in Enhancing Energy Efficiency in Buildings: A Systematic Literature Review. *Energy Science & Engineering*, 14(2), 1036–1066. <https://doi.org/10.1002/ese3.70388>
- Wang, Y., Sun, G., Wu, Y., & Rosenberg, M. W. (2024). Urban 3D building morphology and energy consumption: empirical evidence from 53 cities in China. *Scientific Reports*, 14(1), 12887. <https://doi.org/10.1038/s41598-024-63698-1>
- Weil, C., Bibri, S. E., Longchamp, R., Golay, F., & Alahi, A. (2023). Urban Digital Twin Challenges: A Systematic Review and Perspectives for Sustainable Smart Cities. *Sustainable Cities and Society*, 99, 104862. <https://doi.org/https://doi.org/10.1016/j.scs.2023.104862>
- Wijesuriya, S., Kishore, R. A., Mitchell, M., & Booten, C. (2025). Enhancing EnergyPlus capabilities to model dynamic building envelopes using python plugin. *Energy and Buildings*, 339, 115776. <https://doi.org/10.1016/j.enbuild.2025.115776>
- Wu, A. N., & Biljecki, F. (2021). Roofpedia: Automatic mapping of green and solar roofs for an open roofscape registry and evaluation of urban sustainability. *Landscape and Urban Planning*, 214, 104167. <https://doi.org/https://doi.org/10.1016/j.landurbplan.2021.104167>
- Wu, D., Zheng, A., Yu, W., Cao, H., Ling, Q., Liu, J., & Zhou, D. (2025). Digital Twin Technology in Transportation Infrastructure: A Comprehensive Survey of Current Applications, Challenges, and Future Directions. *Applied Sciences*, 15(4), 1911. <https://doi.org/10.3390/app15041911>
- Wysocki, O., Schwab, B., Biswanath, M. K., Greza, M., Zhang, Q., Zhu, J., Froech, T., Heeramaglore, M., Hijazi, I., Kanna, K., Pechinger, M., Chen, Z., Sun, Y., Segura, A. R., Xu, Z., AbdelGafar, O., Mehranfar, M., Yeshwanth, C., Liu, Y.-C., ... Jutzi, B. (2026). TUM2TWIN: Introducing the large-scale multimodal urban digital twin benchmark dataset. *ISPRS Journal of Photogrammetry and Remote Sensing*, 232, 810–830. <https://doi.org/10.1016/j.isprsjprs.2025.12.013>

- Xu, Y., Litardo, J., Del Pero, C., Leonforte, F., & Caputo, P. (2024). District energy models: A comparative assessment of features and criteria for tools selection. *Energy and Buildings*, 314, 114291. <https://doi.org/10.1016/j.enbuild.2024.114291>
- Xue, F., Lu, W., & Chen, Z. (2020). From LiDAR point cloud towards digital twin city. *ISPRS Journal of Photogrammetry and Remote Sensing*.
- Yadav, Y., Colucci, E., Boccardo, P., & Zlatanova, S. (2024). A Geodatabase Design for the Development of a Digital Twin for Urban Environments: A Case Study from Turin, Italy. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 48(4), 525–532. <https://doi.org/10.5194/isprs-archives-XLVIII-4-2024-525-2024>
- Yüksek, I., & Karadayi, T. T. (2017). Energy-Efficient Building Design in the Context of Building Life Cycle. In *Energy Efficient Buildings*. InTech. <https://doi.org/10.5772/66670>
- Zeng, M., Zhao, F., Zheng, J., & Liu, X. (2013). Octree-based fusion for realtime 3D reconstruction. *Graphical Models*, 75(3), 126–136. <https://doi.org/10.1016/j.gmod.2012.09.002>
- Zhang, J., & Cheng, J. C. P. (2021). Digital Twins for Construction Sites: Concepts, LoD Definition, and Applications. *Automation in Construction*.
- Zhang, J., Zhang, X., Tan, X., & Yuan, X. (2022). Extraction of Urban Built-Up Area Based on Deep Learning and Multi-Sources Data Fusion—The Application of an Emerging Technology in Urban Planning. *Land*, 11(8), 1212. <https://doi.org/10.3390/land11081212>
- Zhang, P., Ghosh, D., & Park, S. (2023). Spatial measures and methods in sustainable urban morphology: A systematic review. *Landscape and Urban Planning*, 237, 104776. <https://doi.org/10.1016/j.landurbplan.2023.104776>
- Zhang, T., Yang, X., Wu, Z., Zhai, G., Doan, D. T., Sun, Q., & Gao, H. (2025). Application of Building Information Modeling for Energy Efficiency: A Systematic Review. *Buildings*, 15(20), 3722. <https://doi.org/10.3390/buildings15203722>
- Zhao, L., Zhang, H., Wang, Q., & Wang, H. (2021). Digital-Twin-Based Evaluation of Nearly Zero-Energy Building for Existing Buildings Based on

- Scan-to-BIM. *Advances in Civil Engineering*, 2021.
<https://doi.org/10.1155/2021/6638897>
- Zhou, B., & Hu, M. (2025). Impact of architectural design elements on the energy efficiency and thermal comfort in neighborhood building ensembles. *Journal of Building Engineering*, 100, 111708.
<https://doi.org/10.1016/j.jobbe.2024.111708>
- Zirak, M., Weiler, V., Hein, M., & Eicker, U. (2020). Urban models enrichment for energy applications: Challenges in energy simulation using different data sources for building age information. *Energy*, 190, 116292.
<https://doi.org/https://doi.org/10.1016/j.energy.2019.116292>

Appendix

A. Courses undertaken for the PhD requirements.

Table 36: Courses completed related to Hard Skills

Hard Skills	Hours
Innovative geomatic techniques for structure, infrastructure, and environmental monitoring	30
Learning by playing: Urban energy transition as a Serious Game	15
BIM and interoperability for SMART Cities processes and Tools	15
Advanced geospatial data management	15
Statistical data processing	20
Python Mega Course	47.5
Open Geospatial Data	15
Drones for 3D multiscale modelling and planning of city and territory	15
Total	172.5

Table 37 : Schedule of courses related to Soft Skills

Soft Skills	Hours
Communication	5
Time Management	2
Public Speaking	5

The new Internet Society: entering the black box of digital innovations	6
Navigating the hiring process: CV, tests, and interview	2
Personal Branding	1
Project Management	5
The Hitchhiker's Guide to the Academic Galaxy	20
Italian Language Level A1	60
Total	106

Table 38: Requirements and completed courses in terms of hours

	Hard Skills	Soft Skills
Minimum requirement	100 hours	40 hours
Completed	172.5 hours	106 hours
Remaining	-	-

B. Research activities undertaken during the tenure of PhD.

Table 39: Participation in external research activities

External Research Activity	Schedule of activity
Point Cloud Processing Workshop, Germany	27 th - 28 th January 2023
euroSDR Seminar, Slovenia	13 th -14 th February 2023
8 th CIPA Spring School, Italy	23 rd -29 th March 2023
euroSDR course: GeoBIM	March 2023
euroSDR course: Point cloud classification	April 2023
Research Internship IIT Roorkee, India	23 rd May 2023 to 25 th August 2023
ISPRS Geospatial Week, Egypt	2 nd - 7 th September 2023
International Forum on Digital Twins, Munich	12 th September 2023

3D GeoInfo Conference, TU Munich	13 th –14 th September 2023
Digital Twins Seminar and Workshop. Faculty ITC, University of Twente, Enschede, Netherlands	19 th -20 th October 2023
2 nd International GEOBENCH workshop, Krakow, Poland	23 rd - 24 th October 2023
3 rd International Conference on Unmanned Aerial Systems in Geomatics, Kuala Lumpur, Malaysia	20 th -21 st November 2023
RIIS Hub project presentations and update, UNSW, Sydney, Australia	14 th March 2024
Digital Twins workshop: 3D spatial challenges and opportunities, UNSW, Sydney, Australia	28 th March 2024
AI Global Summit, Geneva, Switzerland	30-31 May 2024
IEEE IGARSS Summer School, Athens, Greece	4-6 July 2024
ISPRS Technical Commission IV Symposium, Perth, Australia	October 22-25, 2024
ISPRS Technical Commission III Symposium, Belem, Brazil	November 2-7, 2024

Table 40: Research period abroad at other universities

Research Period Abroad	Primary Investigator
Indian Institute of Technology (IIT) Roorkee, India - May 2023 to August 2023	Professor Kamal Jain
University of New South Wales (UNSW), Sydney, Australia – November 2023 to April 2024	Professor Sisi Zlatanova
Delhi Technological University (DTU), New Delhi, India – August 2024 to October 2024	Professor KC Tiwari
Research period at Spatial Data Lab (SDL), Harvard University, USA [Online]	Dr. Yongze Song

C. Recognition and awards during the tenure of PhD.

Table 41 : Recognition and awards during the PhD tenure (2022-26)

Category	Achievement / Role	Institution, Date & Location
Recognition	Invited session on “UAV Remote Sensing and Applications in Civil Engineering”	NIT Kurukshetra, India (MeitY Project) – October 2023
Recognition	Core Organizing Team member for the 3rd International Conference on UASG 2023	Bangi Resort Hotel, Selangor, Malaysia – November 20–21, 2023
Award	Travel Grant Award for IEEE GRSS High Performance and Disruptive Computing School	Santiago de Compostela, Spain – 2025
Other	Teaching Assistantship and Research period at MCG	Delhi Technological University, New Delhi, India
Other	ISPRS Student Consortium Representative at AI for Good Global Summit 2024	Geneva, Switzerland – May 30–31, 2024
Award	Scholarship Award (Rotary International District 2071) to attend CIPA Spring School	Tuscany/Firenze Sud, Italy – 2023
Other	Organizing the “Digital Twins Workshop: 3D Spatial Challenges and Opportunities”	School of Built Environment, UNSW, Sydney, Australia – March 28, 2024

D. Publications and Collaborations during the tenure of PhD.

Below is the summary of publications and collaborations (both already published and in publication pipeline) during the tenure of PhD from November 1st – June 14th, 2026).

Table 42: Publication and Collaborations in Ph.D.

Research Title	Conference/ Journal	Collaborators	Affiliations
<i>Already Published (Online)</i>			
Hybrid Adjustment of UAS based LiDAR and Image Data	<i>ISPRS 2023 Geospatial Week</i>	Yogender Yadav , Bashar Alsadik, Francesco Nex, Fabio Remondino, Philipp Glira	ITC University of Twente Politecnico di Torino FBK Trento Austrian Institute of Technology, Vienna
UseGeo -UAV-based multi-sensor datasets for geospatial research	<i>ISPRS Open journal of photogrammetry and remote sensing</i>	Nex, F., Stathopoulou, E.K., Remondino, F., Yang, M.Y.Madhuana nd, L. , Yogender, Y. , Alsadik, B. , Weinmann, M. , Jutzi, B., Qin, R.	ITC University of Twente Politecnico di Torino FBK Trento University of Utrecht, Netherlands Karlsruhe Institute of Technology, Karlsruhe, Germany The Ohio State University, Columbus, USA
Urban Echoes: Exploring the Dynamic Realities of Cities Through Digital Twins	<i>Lands</i>	Piero Boccardo, Luigi La Riccia, Yogender Yadav	Politecnico di Torino, Italy
Integration of iPhone LiDAR with Quadcopter and fixed-wing UAV Photogrammetry for the Forestry Applications	<i>ISPRS International GEOBENCH workshop 2023</i>	Yogender Yadav , Sunni Kanta Prasad Kushwaha, Martin Mokros, Juliana Chudá, Marek Pondelík.	Politecnico di Torino IIT Roorkee, India Technical University in Zvolen, Slovakia Czech University of Life Sciences, Prague

Turin Digital Twins: Initiatives and Challenges	<i>AIT conference 2023</i>	Luigi la Riccia , Vittorio Scolamiero, Yogender Yadav , Allegra Eusebio	Politecnico di Torino
Aerial LiDAR And Infrared Thermography for Urban-Scale Energy Assessment and Planning	<i>AIT conference 2023</i>	S. Anselmo, M. Ferrara , Yogender Yadav	Politecnico di Torino
Assessing Photovoltaic Potential in Urban Environments: A Comparative Study between Aerial Photogrammetry and LiDAR Technologies	<i>ISPRS TC IV Symposium 2024</i>	Yogender Yadav, Harshit, Piero Boccoardo, Sisi Zlatanova, Kamal Jain	Politecnico di Torino, Italy UNSW Sydney, Australia IIT Roorkee, India
Development of 3D Urban Digital Twins for Traffic Monitoring in Unreal 5 Game Engine	<i>ISPRS TC IV Symposium 2024</i>	David Crampen , Yogender Yadav , Shofia Ishar, Wenwen Tian, Sisi Zlatanova	RWTH Aachen, Germany Politecnico di Torino, Italy UNSW Sydney, Australia China University of GeoSciences, Wuhan, China
A Geodatabase Design for the Development of a Digital Twin for Urban Environments: Case Study from Torino, Italy	<i>ISPRS TC IV Symposium 2024</i>	Yogender Yadav , Elisabetta Colucci, Piero Boccoardo, Sisi Zlatanova	Politecnico di Torino, Italy UNSW Sydney, Australia
A Data Model for Unrecognised Historical Neighbourhood (Case study: Telukbetung, Indonesia)	<i>ISPRS TC IV Symposium 2024</i>	Shofia Ishar, Sisi Zlatanova, Yogender Yadav	UNSW Sydney, Australia Politecnico di Torino, Italy
Evaluating the Potential of Nature-Based Solutions (NBS) and Solar Energy in Urban Built Environments with 3D Point Clouds: Insights from Torino, Italy	<i>ISPRS TC IV Symposium 2024</i>	Sara Biancifi ori, Yogender Yadav , Piero Boccoardo, Sisi Zlatanova, Adriano Bisello	EURAC, Bolzano, Italy Politecnico di Torino, Italy UNSW Sydney, Australia

Unleashing the Dynamic Strategies in the Era of Change – A Spotlight on the ISPRS Student Consortium's Global Contributions	<i>ISPRS TC III Symposium 2024</i>	Yogender Yadav , Laxmi Thapa, Nicolas Pucino, SKP Kushwaha, Miguel Luis Rivera Lagahit, Chukwuma John Okolie	Politecnico di Torino UNSW Sydney, Australia Aston University, Birmingham, UK The Australian National University, Canberra, Australia IIT Roorkee, India Tokyo Institute of Technology, Japan University of Lagos, Nigeria
<i>Within Publication Pipeline</i>			
Integration of Mobile Frame Camera and Aerial Photogrammetry for Feature Height Estimation	<i>UASG Conference 2023 (Available online in July 2026)</i>	Yogender Yadav , Vittorio Scolamiero, Luigi La Riccia and Piero Boccardo	Politecnico di Torino
“How to” of Digital Twins: A geospatial perspective for the reproducibility of Digital Twins (DT)	<i>IJGI (Ready to Submit)</i>	Yogender Yadav , Federica Gaspari , Abhishek Rai, Mansi Nagpal, Yongze Song, Sisi Zlatanova, Piero Boccardo	Politecnico di Torino Politecnico di Milano IIT Roorkee, India Georgia Institute of Technology Curtin University, Perth UNSW Sydney
Challenges and Opportunities in Creating 3D Urban Digital Twins	<i>Remote Sensing (ready to submit)</i>	Yogender Yadav , Sisi Zlatanova, David Campren, Harshit, Shofia Ishar, Shabnam Jabari, Piero Boccardo, Luigi La Riccia	Politecnico di Torino, Italy UNSW Sydney, Australia RWTH Aachen, Germany IIT Roorkee, India University of New Brunswick, Canada