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The Use of BIM Models and Drone Flyover Data in Building Energy Efficiency Analysis

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Abstract

Building information modeling (BIM) and thermal imaging from drone flyovers present innovative opportunities for enhancing building energy efficiency. This study examines the integration of BIM models with thermal data collected using unmanned aerial vehicles (UAVs) to assess and manage energy performance throughout a building's lifecycle. By leveraging BIM's structured data and the concept of the digital twin, thermal analysis can be automated to detect thermal bridges and inefficiencies, facilitating data-driven decision-making in sustainable construction. The paper examines methodologies for combining thermal imaging with BIM, including image analysis algorithms and artificial intelligence applications. Case studies demonstrate the practical implementation of UAV-based thermal data collection and BIM integration in an educational facility. The findings highlight the potential for optimizing energy efficiency, improving facility management, and advancing low-emission building practices. The study also addresses key challenges such as data standardization and interoperability, and outlines future research directions in the context of smart city applications and energy-efficient urban development.

Keywords: artificial intelligence; building information modeling; digital twin; drones; energy efficiency; IFC; sustainability; thermography; thermal bridges; UAV

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1. Introduction

1.1. BIM and Energy Efficiency

The Architecture, Engineering, and Construction (AEC) industry has increasingly adopted technologies such as building information modeling (BIM), lean construction methods, prefabrication, and modular systems in response to the accelerating pace of development change. Simultaneously, the sector is undergoing a broader digital transformation, driven by innovations associated with Industry 4.0, including digital twins (DTs), Cyber–Physical Systems (CPSs), virtual reality (VR), augmented reality (AR), and computer vision technologies [1]. These digital tools offer significant potential for addressing challenges such as building energy consumption [2]. Given the escalating concerns over climate change, improving energy efficiency has become an important priority within the built environment. Using simulation tools and data-driven decision-making processes enables

more accurate predictions and optimisations of a building's energy performance throughout its lifecycle. In particular, BIM represents a sophisticated digital design methodology integrating architectural, structural, and systems information into cohesive 3D models. By consolidating vast design data, BIM enhances planning, simulation, and interdisciplinary coordination efforts. Identifying key BIM-related factors influencing environmental threat assessment is essential to advancing innovation and promoting sustainable development within the AEC sector [3–5].

Integrating BIM with sustainability assessments enhances the design of eco-friendly buildings by enabling continuous monitoring and identifying areas for improvement. This approach supports better environmental performance; promotes green practices; and facilitates scenario analysis for optimizing energy use, material selection, and sustainability. Even those with limited experience can implement steps to meet sustainability standards and achieve improved environmental outcomes [6–11].

Using BIM for energy efficiency assessment is challenged by a lack of interoperability between software, as the data exchange is not seamless. Accurate energy analysis requires detailed inputs, which are often missing or inconsistently defined in early BIM models [12]. Moreover, energy efficiency is often addressed later in the design process, and BIM's full potential can be missed when energy simulations are not integrated from the early conceptual stages.

1.2. UAV-Based Thermal Imaging in Building Analysis

Unmanned Aerial Vehicles (UAVs) equipped with thermal imaging technology have emerged as a transformative tool for building energy efficiency analysis. UAV-based thermography offers significant advantages in identifying thermal bridges, which are critical for optimizing energy performance. Gathered data serves as a starting point for thermal audits of existing buildings and supports informed decision-making. UAVs enable comprehensive inspections of building envelopes by capturing thermal images from various angles and elevations, facilitating the detection of issues in hard-to-reach areas, such as tall buildings and rooftops. In addition, compared to terrestrial methods, UAVs provide consistent spatial resolution across building surfaces while reducing inspection time and labor intensity. Recent research is contributing to the improvement in technology, making the entire process more efficient. For instance, Zhang's study proved that complex geometry is not an obstacle when UAV images with BIM are used in Structure-from-Motion [13].

Using UAVs for thermal imaging in building analysis presents several challenges that impact the accuracy and efficiency of inspections. One primary issue is the sensitivity of thermal cameras to motion and vibrations caused by UAV flight, which can lead to blurry images and reduced data quality. Additionally, the dependency on favorable weather conditions limits the operational flexibility of UAVs, as inspections are often restricted to specific times or days. For best results, the temperature difference between the interior and exterior of an examined building should exceed 8 °C [14]. Furthermore, thermographic cameras often struggle with reflective surfaces, such as mirrored façades, which interfere with thermal readings and reduce measurement reliability. Finally, the inability of UAV-based thermal imaging to measure the thickness or depth of thermal issues highlights its limitations in providing a comprehensive thermal audit. Addressing these challenges requires advancements in camera technology, flight protocols, and regulatory frameworks to fully realize the potential of UAV-based thermal imaging in building analysis. One possible solution is also to leverage multimodal data fusion techniques used by UAVs [15].

1.3. Thermal Bridges

Building energy efficiency can be significantly impacted by thermal bridges, which can lead to increased heat losses or condensation issues. Although novel construction materials, especially high-performance insulation, and modern construction techniques are designed to reduce the risk of their occurrence, they cannot be eliminated. Additionally, the accurate assessment of thermal bridges poses challenges [16]. An additional challenge is accurately mapping data related to thermal bridges to specific areas of the building structure, ensuring that the data obtained from thermographic imaging is truly useful. A potential remedy for this issue may be the use of BIM, which supports this at various stages of the construction process—from the design phase, where energy efficiency should be taken into account, through quality control of insulation and installation work during the construction phase, all the way to the building management phase. BIM enhances thermal simulations by integrating geometry and material data, improving 2D and 3D thermal bridge analysis. This automation streamlines identification, calculation, and early-stage energy optimization in building design [17]. BIM is increasingly used to integrate Building Energy Modeling (BEM) and Simulation (BES) to enhance energy efficiency [16]. The BEM model can help estimate electricity use intensity (EUI) and evaluate energy-saving potential. Integrating UAV-BIM-BEM creates an opportunity to develop seamless cooperation [18]. BIM-based BEM overcomes traditional modeling limits, improves consistency, and reduces costs [18]. Advanced sensor technology and data processing techniques have made the integration of thermography point clouds and BEM possible, resulting in systems capable of the real-time thermal monitoring of construction sites by combining thermal imaging with 3D mapping [19].

The building and energy retrofitting industry is undergoing a significant digital revolution, integrating infrared thermography, photogrammetry, and enriched three-dimensional models. Thermography is established in this scenario as an essential diagnostic methodology for examining the thermal behavior of buildings non-invasively [20]. Its ability to make thermal bridges, heat losses, humidity, and other imperfections invisible to the human eye makes it a key method for planning more effective, sustainable rehabilitation interventions based on objective data [21].

On the other hand, including these thermal images in three-dimensional digital models, such as point clouds or digital twins, enables the visualization, quantification, and communication of a building's energy status in an integrated way [22]. This coupling of thermography and digitalization constitutes a qualitative leap in energy efficiency project planning and implementation, by providing a sound technical basis for decision-making in the diagnosis and intervention stages.

1.4. The Significance of Energy Efficiency Throughout the Entire Life Cycle of Buildings

Since buildings account for approximately 35% of the total energy consumption, designing and constructing highly energy-efficient buildings has emerged as a key objective in the construction industry [23]. The European developed the framework, to assess the full life cycle of buildings. This methodology segments the building's life cycle into four phases: production, construction, operation, and end-of-life, specifying the carbon emissions associated with each stage. In the classification of building energy consumption, a distinction is made between embodied carbon emissions, related to the construction phase, material production, transportation, and maintenance and operational carbon emissions, responsible for energy consumption related to building heating, cooling, and energy use throughout its entire lifecycle [24]. For the design of energy-efficient building stock, advanced architects utilize intelligent algorithms to strike an optimal balance between energy consumption, daylight illuminance, cooling and heating loads, and thermal comfort. Advanced soft-

ware tools allow for such calculations, for example, the Grasshopper plug-in embedded in Rhinoceros 8 software, which enables parametric design [25]. Equally important is the low-emission nature of the building's construction phase. To reduce embodied carbon emissions, recycled materials are used, which, due to legal restrictions, may not always be applicable to the structural elements of the building itself. However, they can successfully be applied in constructing elements around the building, such as recycled aggregates (concrete) for pavement construction [26]. The quality of construction work also plays a crucial role in this phase—for example, ensuring the continuity of the insulation layer, eliminating thermal bridges, and properly installing windows. In the operational phase of the building, achieving a low-emission or zero-energy building depends on the use of renewable energy sources (e.g., photovoltaic panels) as well as energy-efficient systems for ventilation, air conditioning, and heating [27].

Correcting thermal anomalies, such as thermal bridges, uncovered insulation gaps, or poor envelope junctions, based on thermographic inspection can significantly reduce energy demand during the operational phase of a building. These operational improvements directly translate into CO_2 emission reductions when energy sources are carbon-intensive. Recent studies demonstrate that thermal envelope upgrades guided by precise diagnostics can reduce operational energy use by 10–30%, corresponding to substantial lifecycle emission savings, particularly in heating-dominant climates [28]. Integrating UAV-based thermographic data into BIM workflows facilitates such targeted upgrades, aligning the building design and retrofitting process with low-carbon development goals.

1.5. The Aim of the Study

The study aims to develop and evaluate methodologies for integrating building information modeling (BIM) with thermal imaging data acquired through UAVs to support building energy efficiency analysis. The research examines how structured BIM data can be integrated with thermal imaging, advanced image processing techniques, and AI tools to identify thermal anomalies, such as thermal bridges, across the various phases of a building's lifecycle.

Through case studies, particularly within the BUILDSPACE project framework, the study demonstrates the practical application of these technologies in real construction scenarios. The research assesses the effectiveness of integrating thermographic information with enriched digital twin models and evaluates proposals for extending openBIM standards, such as IFC 4.3, to better accommodate thermal data.

The broader goal is to support sustainable construction practices, improve facility management through data-driven decision-making, and contribute to the development of smart cities by enhancing building energy performance monitoring and optimization.

The methodological novelty of the present research, therefore, lies in an end-to-end pipeline that (1) registers georeferenced thermographic orthomosaics to an IFC-compliant BIM, (2) enriches BIM elements with quantitative surface-temperature and anomaly metadata, and (3) demonstrates bidirectional data flow between the enriched BIM and an EnergyPlus-based BEM. Neither Zhang et al. (2025) [13] nor Zhang et al. (2023) [14] offer this combination of semantic enrichment, openBIM compliance, and energy-simulation feedback. Consequently, the following study delivers an interoperable workflow linking UAV thermography with actionable energy efficiency interventions

2. Literature Review

2.1. BIM and Energy Efficiency in Building Design

BIM, combined with Building Energy Modeling (BEM), enables the detailed computational analysis of energy consumption during the design phase. This integration helps

architects and engineers simulate energy performance, optimize building automation systems, and minimize energy use. However, challenges such as interoperability between BIM and BEM tools remain a hurdle for seamless data exchange [29]. Advanced visual programming environments, such as Dynamo, integrated with building information modeling (BIM) platforms like Revit, automate the selection of energy-efficient thermal insulation materials. This process improves the thermal performance of building envelopes and reduces energy consumption. Dynamo scripts have been developed to streamline thermal engineering calculations and create reusable libraries of insulation materials [30]. BIM facilitates the evaluation of carbon emissions throughout a building's lifecycle by combining Life Cycle Assessment (LCA) methodologies with architectural information management. This integration supports environmentally friendly design decisions, contributing to sustainable construction practices [31].

However, some challenges, such as a lack of seamless data exchange between BIM and other modeling tools, limit its full potential in energy-efficient design. Projects with short life cycles may not benefit from the extensive modeling capabilities of BIM due to time constraints [29]. Further research is needed to integrate renewable energy systems into BIM workflows for holistic sustainability [31,32].

2.2. Digital Twin as an Extension of BIM in Energy Management

Digital twin technology, as an extension of BIM, is revolutionizing energy management in buildings by enabling real-time monitoring, predictive analytics, and the optimization of energy consumption. By integrating building information modeling (BIM) with Internet of Things (IoT) sensors, machine learning, and artificial intelligence, DT creates a dynamic digital replica of a physical building that continuously updates based on real-world data. This capability allows for precise energy forecasting and optimization, reducing energy consumption by up to 20% in some applications, as demonstrated in mega-facility management studies [33,34].

In energy-efficient building design, DT enhances the predictive capabilities of BIM by simulating various operational scenarios and evaluating their impact on energy performance [35]. For instance, DT platforms can monitor real-time power consumption and environmental parameters, using advanced machine learning models like neural networks to predict and optimize energy usage with high accuracy [36]. Moreover, DT technology facilitates the integration of renewable energy systems and supports lifecycle carbon footprint analysis, aligning with sustainability goals such as the European Union's climate neutrality targets [37].

Additionally, DT's ability to integrate extended reality (XR) technologies further enhances its utility in facility management by improving maintenance operations and enabling remote collaboration. This combination ensures that smart buildings operate efficiently and adapt dynamically to changing conditions, reducing greenhouse gas emissions and operational costs [38]. Digital twin technology extends the capabilities of BIM into a comprehensive framework for proactive, sustainable energy management.

By integrating BIM's data—such as geometries, materials, and thermal properties—with real-time data from IoT devices, digital twins create virtual replicas of existing buildings. This fusion enables continuous monitoring and predictive analytics, addressing inefficiencies and optimizing energy consumption patterns [39].

The application of artificial intelligence (AI) further enhances this framework by enabling advanced functions such as simulations and predictions, which help improve HVAC performance and overall energy efficiency in material buildings [35]. Simulations are based on occupancy patterns, external conditions, and energy consumption data [39].

2.3. Thermography Data Integration with the BIM Model

The research on integrating the data obtained from thermographic inspection of the building is not extensive. The possible methodologies include integrating thermal visualization and measurements into an orthomosaic linked with the corresponding BIM model. The enrichment of the BIM model with thermography data was presented as feasible by 'translating 3D surface thermal profiles into energy performance metrics and mapping them to BIM elements' [19]. The other approach involved the fusion of thermographic data captured by UAV with RGB images, creating a basis for thermal-textured BIM generation [40]. A thermal-textured BIM model was obtained using a Dynamo script prototype, providing a thermal image layer on the building elevation view [41]. Other research proposes a method for mapping thermal anomalies captured by UAVs onto BIM models by modeling them as BIM objects. The thermal images are first processed using a deep learning-based instance segmentation model to extract relevant features, which are then integrated into the BIM model with corresponding information accurately mapped to their locations [42].

An analogy can be observed in the approach to mapping thermographic data collected for the external envelope of the building and other types of building inspections, such as seismic damage assessment [20] or other types of façade defects. In each of these cases, the integration of data from captured images is associated with BIM through overlaying, linking, or coloring/texturing surfaces [41], thus enabling the integration of this information within the 3D BIM model. It follows that the focus in these studies is on the thermal image itself and its overlay onto the BIM model, rather than mapping the thermal values to the properties of specific BIM model elements, as presented in case study 2, discussed later in the article. Less emphasis is placed on mapping and enriching the informational layer and classifying BIM models—assigning specific temperature or anomaly values to the properties of individual BIM elements that constitute an integral part of the BIM information model. An example is a system that generates a 3D thermal model and calculates actual thermal resistances using digital and thermographic images, as well as environmental data, thereby automating the updating of thermal properties for BIM elements. The above is performed by linking the results to the gbxml components [43]. As presented later in the article, in case study 1, this research demonstrates the integration of a visual thermographic representation overlaid onto the BIM model, along with an option for automatic temperature readings and the ability to mark thermal bridges directly on the building model, including the indication of thermal anomalies. In turn, case study 2 explores the possibility of assigning data obtained from thermography to the BIM model in the IFC format—an aspect not considered in previous research. This approach makes these considerations a novel contribution compared to the existing literature.

Recent studies highlight the growing integration of UAV technologies with BIM for monitoring energy and environmental performance. According to research [44], by 2022, only one study systematically addressed the use of UAVS combined with thermal imaging for building energy diagnostics. This indicates a significant research gap. More recent investigations recognize the potential of UAV-based thermal inspections for improving energy assessments [45].

The Scan-to-BIM methodology employs UAV data acquisition with three types of sensors: LiDAR, RGB imaging, and radiometric thermal infrared sensors capable of capturing 360-degree scans via dual-axis rotation [46]. This multimodal approach enables the semantic segmentation of scanned data, allowing for automatic and accurate thermal calculations integrated into BIM models.

Furthermore, UAV-integrated thermal monitoring contributes to the early detection of thermal anomalies, thereby informing targeted retrofit strategies [47]. Recent research has also demonstrated that combining artificial intelligence (AI) and machine learning

techniques with UAV-BIM workflows enhances diagnostic accuracy and predictive capacity for energy performance evaluations [48].

2.4. Digital Tools for Thermographic Assessment

Infrared thermography has long been recognized as a reliable and non-invasive technique for identifying thermal anomalies in building envelopes. Thermography enables the detection of thermal bridges, moisture, air leakages, and heat losses—issues that often remain invisible to the naked eye yet have significant implications for building energy performance [49]. Its application supports evidence-based approaches to retrofitting by providing objective, quantifiable data that inform rehabilitation strategies.

Recent advancements in data acquisition techniques have highlighted the use of drone-mounted sensors for thermographic surveys. This approach offers greater flexibility and coverage, especially when combined with RGB imaging and RTK (Real-Time Kinematic) geolocation technology. The literature stresses the importance of conducting drone-based and robotic thermal surveys under controlled weather conditions to ensure accuracy and repeatability [50–53]. Recommended practices include flying during windless and overcast days to minimize external thermal interference and selecting the time of day tailored to seasonal thermal gradients. Image acquisition is performed in RAW or radiometric format, which preserves thermal fidelity and allows post-processing calibration.

The construction of accurate 3D models from aerial imagery relies on meticulous data handling. Procedures such as ground control point (GCP) placement and image overlap management ensure spatial precision during photogrammetric reconstruction [54]. These spatially referenced models are the foundation for integrating thermographic data into enriched three-dimensional visualizations.

Thermal data acquisition, processing, and visualization methods, combined with three-dimensional spatial modeling, provide the foundation for a more precise and integrated analysis of building energy efficiency. Integrating thermal images with digital models—particularly drone flight data and BIM technology—enables the accurate localization of thermal bridges, heat losses, and other thermal anomalies.

2.5. Machine Learning in Thermal Image Analysis

Recent advancements in machine learning (ML) show potential for enhancing the assessment and prediction of thermal performance in individual buildings and broader urban environments [55]. Integrating ML algorithms with data from thermal imaging and environmental sensors makes it possible to model current thermal conditions and forecast future scenarios under varying operational or climatic contexts [56]. These systems allow for the rapid analysis of large, multidimensional datasets, uncovering complex relationships between environmental variables and thermal behavior.

Machine vision supports the monitoring and analysis of heat flow inside buildings by recording and processing temperature distribution data in real time [57]. Using high-resolution cameras enables the detailed mapping of the distribution of thermal energy, allowing for the visualization of changes in heat flow. This gives information about the circulation of thermal energy in rooms, supporting the optimization of indoor conditions and increasing energy efficiency and user comfort [58]. Visualization technologies play a significant role in optimizing the thermal environment of buildings by offering intuitive ways to analyze and present data. They enable designers and decision-makers to better understand the thermal behavior of buildings through graphical representations of thermal parameters, which helps them make informed design decisions. With such tools, it is possible to easily identify problem areas and quantify energy efficiency, resulting in more effective strategies to enhance occupant comfort and reduce energy consumption [59].

The study on traditional Japanese wooden houses presented an approach that combined in situ measurements with machine learning methods. Using predictive models such as SVR (Support Vector Regression) and RFR (Random Forest Regression) allowed for the prediction of room temperature based on external factors and thermal interactions between adjacent rooms. A key element was the use of feature significance analysis, which revealed a strong influence of the temperature of the adjoining room on the temperature forecast in the analyzed interior—a phenomenon also confirmed by thermal imaging, which showed heat losses through gaps in fusuma partitions. Including thermal imaging techniques in validating predictive models emphasizes the growing importance of integrating measurement data and machine learning algorithms to identify thermal bridges and areas requiring improved insulation [60].

On an urban scale, the thermal comfort prediction model may provide valuable insights for urban heat management by generating personalized thermal comfort maps for different city areas under projected weather conditions [61]. This information aids in understanding the spatial distribution patterns of thermal comfort perceptions across urban areas, identifying key influencing factors, and offering scientific guidance for optimizing the urban thermal environment [62].

The review in this section provides a foundation for future work in this domain. The integration of machine learning models, such as Convolutional Neural Networks (CNNs) for thermal anomaly segmentation or regression-based models like Random Forests for surface temperature prediction, has shown promising results in related research. For instance, Tan et al. [42] demonstrated the use of deep learning-based instance segmentation models to extract façade anomalies from UAV thermal images and integrate them into BIM workflows. Similarly, Shrestha and Shimizu [60] validated Support Vector Regression and Random Forest Regression for predicting thermal performance in traditional Japanese houses using thermal imaging data. These studies confirm the potential of AI for automating anomaly detection and supporting BIM enrichment workflows [39,57].

2.6. Research Gap and Novelty Statement

While prior research has demonstrated partial efforts to overlay thermal images on BIM models, few studies have explored the integration of thermographic data directly into the IFC information structure or proposed openBIM-compatible semantic models for thermal data representation. Moreover, the manual mapping of thermal values to BIM elements remains underexplored, particularly in the context of IFC 4.3 and bSDD-based classification. This positions our research as a novel approach that bridges current limitations in semantic thermal data integration with building information modeling workflows.

While the research aims to develop and evaluate methodologies for BIM-UAV integration, it is essential to define the research questions: What is the current state of research on integrating data obtained from drone flights with BIM? How can thermographic data be visualized on a three-dimensional building representation for thermal bridge analysis (as in case study 1)? What would a framework look like that allows for the integration of thermographic data obtained from drone flights with the information layer (classification) of the model in IFC format (case study 2)?

Although Sections 2.1–2.5 review UAV thermography, BIM enrichment, and AI-driven anomaly detection, an explicit theoretical lens is still needed to explain how these domains interact to reduce the impact of thermal bridges.

Figure 1 organizes the workflow into three layers and two feedback loops: data acquisition layer—radiometric thermal + RGB imagery captured by UAVs, co-registered into a georeferenced 3D point cloud; semantic integration layer—calibrated temperature

values written into IFC 4.3 property sets; and decision impact layer—query-ready thermal attributes feed BEM simulations and retrofit planning; anomalies verified by the next UAV survey close the learning loop. The model is grounded in the Information Transformation Theory (sensor data → structured knowledge) and Feedback Control Theory (iterative anomaly mitigation), providing a causal chain from field data to energy-savings metrics. Embedding numeric temperature attributes (as opposed to textures) reduces data-to-insight latency. The following is a conceptual model linking UAV thermography, BIM enrichment, and energy efficiency outcomes.

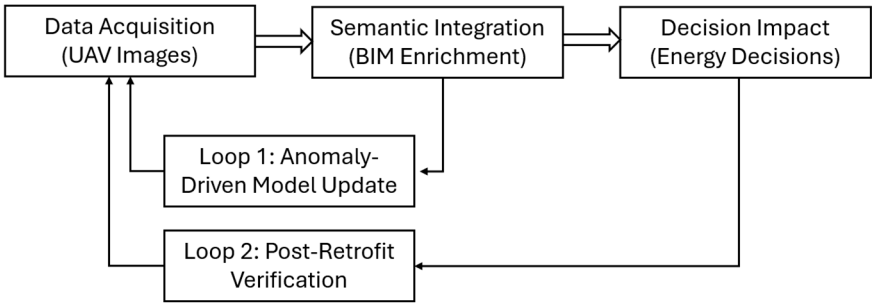


Figure 1. Conceptual model of the UAV-to-BIM pipeline for thermal bridge detection and retrofit. Verification [source: authors].

3. Research Methods and Materials

The methods employed in this research include a literature review, qualitative analysis of case studies, and comparative evaluation of experimental outcomes. The primary focus was on innovations in BIM, thermal imaging, UAV applications, and energy efficiency strategies.

The literature review was based on a comprehensive analysis of primary sources and the recent scientific literature, enhancing the study's credibility and reliability. Only peer-reviewed articles published within the last five years and the results of research projects and grants accessible to the authors were considered.

The selection of the building for case studies (1 and 2) was based on relevance to the research objectives, data availability, and the ability to test the complete UAV-to-BIM workflow. The cases are examples of buildings integrating UAV thermal imaging with building information modeling (BIM). Case study 1—The Warsaw Pilot—provided a representative example of a modern, multi-story university building incorporating low-energy technologies. Since the building is intended to meet the requirements for BREEAM certification, high execution quality had to be ensured. Energy-efficient design goals prompted drone flights during construction to verify the quality of work performed on the construction site and detect potential thermal bridges. In evaluating technical case studies, including those developed within the BUILDSPACE project, detailed descriptions of the employed research methods, IT tools, programming environments, and test parameters were provided. Different software environments were employed at various stages of data processing, including open-source tools such as ImageJ 1.54n for thermal data calibration, photogrammetric reconstruction software, and custom-developed solutions for integrating thermal and geometric data into enriched 3D models.

The effectiveness of the applied methods was verified using commonly accepted performance indicators described within each case study. Comparative analysis against the results reported by other researchers further validated the methodological robustness. For case studies involving thermal anomaly detection and energy performance evaluation, assessment metrics such as spatial accuracy, temperature calibration precision, and detection rates of thermal bridges were considered. The research methodology thus combined

literature-based critical review with empirical analysis of case study implementations, ensuring a balanced and rigorous approach to addressing the research objectives.

The practical application of data acquired from the UAV-captured thermography of the building for energy efficiency analysis in a 3D model is presented in case study 1. The next step—UAV data integration with BIM—was presented and validated in case study 2, focusing on transferring and presenting the acquired thermographic information within the IFC file. As the existing research mainly addresses the mapping of geometric thermal representations into BIM, and there are currently no established guidelines for describing thermographic data within the classification of building elements, case study 2 focused on the information structure and the assignment of values extracted from thermographic imagery to the parameter layer of the BIM model using open BIM standards (IFC and bSDD).

The workflow from UAV data acquisition through thermal 3D representation up to 3D thermal model representation and integration with BIM is as shown below:

(A) Thermal activation of the building—increasing indoor temperature to create a measurable temperature gradient.
(B) UAV flight planning—planning flights (general, roof, and façade) to ensure 70–80% image overlap; defining flight paths, angles, and distances (5–20 m depending on type).
(C) Environmental data logging—recording ambient temperature and humidity during each flight.
(D) Data acquisition (RGB + Thermal)—executing pre-programmed/manual UAV flights with RTK activated for accuracy.
(E) Thermal image preprocessing—utilization of ImageJ and the IRImage plugin for calibration and conversion to temperature maps.
(F) Three-dimensional model reconstruction—generation of a 3D model from RGB images via Structure from Motion (SfM).
(G) Thermal–RGB Fusion—registering thermal data onto the 3D model using custom software to create a thermal point cloud (X, Y, Z, RGB, and temperature).
(H) (H1) Visualization in Potree—visualizing and analyzing thermal anomalies interactively using color maps, measurement tools, and layer overlays (e.g., RGB and thermal).
(H2) Integration with BIM (IFC)—manually assigning temperature data and thermal anomaly types to specific building elements in the IFC model (e.g., walls and windows), using predefined bSDD properties (e.g., via Blender and Bonsai plugin).

3.1. Case Study 1: BUILDSPACE Project

The practical implementation of the use of drone flyover data in building energy efficiency analysis was presented in the innovation developed within the Horizon Europe project, BUILDSPACE, financed by the EUSPA European Program, which 'aims to develop innovative applications to support buildings' energy efficiency and cities' resilience and sustainability'. Focused on satellite data analysis, the project combines photogrammetric and thermal data captured by drones with digital twins and augmented and virtual reality, aiming to provide cutting-edge services for monitoring the energy performance of buildings and entire cities. In 5 services—2 for the building level and 3 for the city level—the project's goals align with actions raised for maintaining resilient and sustainable buildings and cities, highlighting the significance of the urban thermal environment and the risk of flooding [Concept | BUILDSPACE].

The outcome of the project is the BUILDSPACE platform, combining 5 services that play the role of a decision support platform offered to Building Value Chain stakeholders (e.g., urban planners, representatives of the construction sector, the renovation of buildings

sector, city authorities, NGOS, SMES in the industries mentioned above, policy makers, and researchers). Both the research and practical aspects of the project are significant; therefore, 1 of the 5 project objectives declared is 'To test and evaluate the services with the relevant stakeholders in 4 pilots across EU and pave the way for their exploitation and sustainability plans' [Objectives | BUILDSPACE]. Demonstration and implementation of the technology developed are performed by 4 consortium representatives: Mostostal Warszawa SA in Poland (Warsaw and Poznan), Municipality of Piraeus in Greece (Piraeus), Riga Planning Region in Latvia (Riga) and IMZI—Blue-green Infrastructure Institute in Slovenia (Ljubljana).

3.1.1. Case Study of the Warsaw Pilot

Given that the paper's topic examines the analysis of building energy efficiency using BIM models and drone flyover data, the selected case study was the Faculty of Psychology of the University of Warsaw's Pilot site building (Figure 2). The pilot took place during the construction process of the educational building. The University of Warsaw campus features six above-ground stories and two underground stories. The building spans nearly 3000 m^2, with a total overground area of over 17,500 m^2, an underground area of over 9000 m^2, and almost 122,500 m^3. The building is designed to accommodate 30 classrooms for lectures, seminars, and computer classes, as well as rooms for quiet work and a lecture hall that can accommodate nearly 400 people. The building also features laboratories adapted for conducting individual and group research, as well as an urban farming community garden on the roof. The project includes solutions for sustainable development and environmental protection, e.g., energy-saving electrical installations, heat recovery systems, and renewable energy sources.

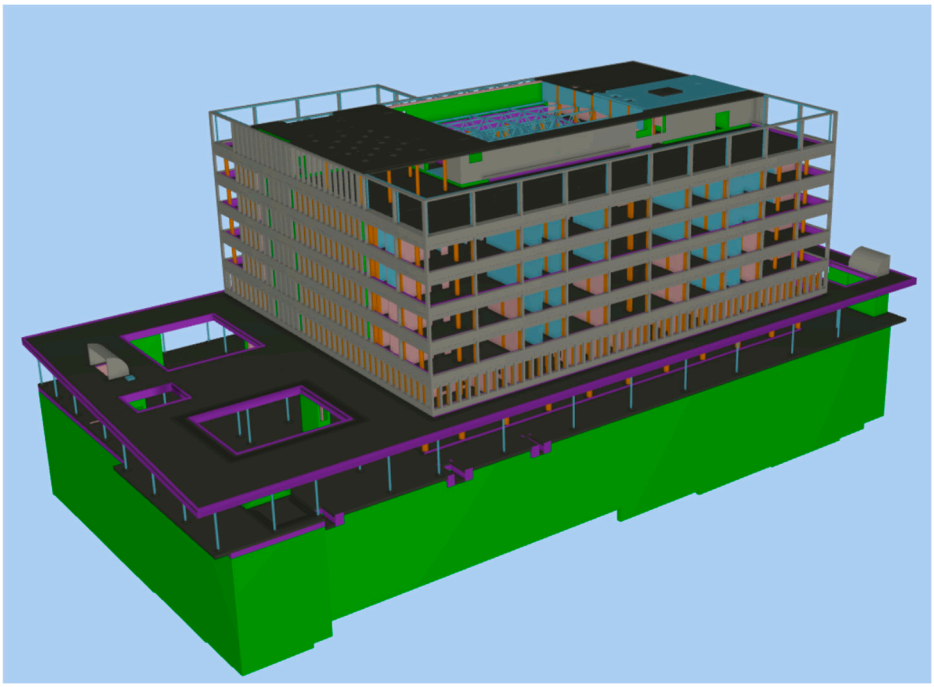


Figure 2. The IFC model of the structural elements of the Faculty of Psychology of the University of Warsaw [source: with the consent of Mostostal Warszawa SA].

Within the BUILDSPACE project, this pilot deployed the services at the building level (DT generation and DT enrichment). It implemented Service 2, which aims to analyze and assess the building's energy performance, particularly by verifying the quality of

construction works through the early detection of deviations from the intended design and identifying thermal bridges using thermography.

3.1.2. Application of Thermal Data Collection Methodology

In this context, thermal data was gathered using remote sensor-based techniques on drones. The approach specifies that weather conditions should be strictly controlled for reliable data acquisition [63]. Campaigns were conducted during cloudy, windless days, reducing the effects of direct solar radiation and thermal turbulence in the environment. In winter, sunrise and sunset times are preferred, when the indoor–outdoor temperature difference is more pronounced [14]. Nighttime flights were chosen in summer, making it possible to observe heat islands and thermal accumulation in low-inertia materials.

The photographs were shot in RAW or radiometric mode to preserve the integrity of the thermal signal by applying subsequent corrections and calibrations without loss of quality [64]. Each photograph was accurately georeferenced using RTK (Real-Time Kinematic) technology, reducing positional error to a few centimeters. This positional information is required to maximize its subsequent integration in three-dimensional photogrammetric models [65].

Ground control points (GCPs) were placed around the building to ensure an accurate reconstruction of the built environment. With the points strategically placed at different heights and orientations, the three-dimensional model could be referenced to real-world coordinates, maintaining the scale, proportions, and spatial location of the object represented [66].

3.1.3. Procedures for Thermal Data Acquisition

Thermal imaging was conducted through manual and pre-programmed drone flights with UAVs equipped with RGB and thermal imaging sensors. UAVs are practical tools for energy audits and building inspections, especially when equipped with thermographic cameras, which enable efficient data collection and reduce safety risks. The images must be calibrated and cropped to represent surface temperature distributions [52] effectively.

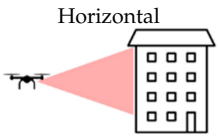
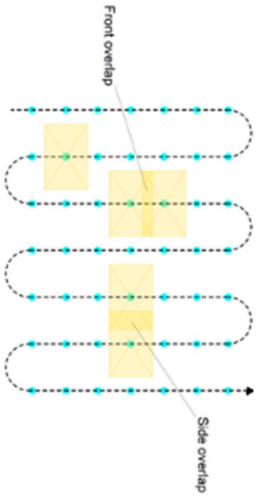
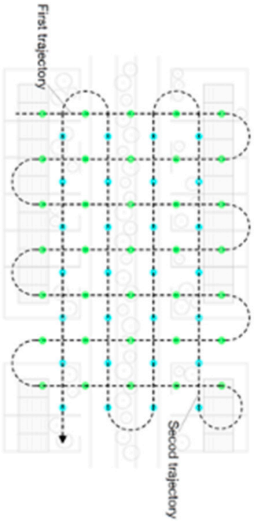
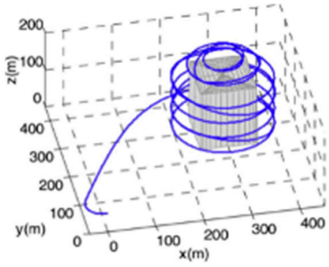
In aerial surveys, efficient UAV flight planning emphasizes overlap, coverage, and orientation to ensure coherent 3D reconstruction. Where manual imaging of the ground floor is performed, care should be observed to maintain continuity and ensure proper overlap with images of upper levels to avoid misalignment during thermal model reconstruction [67].

A constant and precisely regulated distance from the building envelope must be maintained throughout the entire flight trajectory, particularly for manual flights. The Real-Time Kinematic (RTK) positioning system also must be activated to reduce geolocation errors in the resulting 3D model. Ambient conditions, including temperature and relative humidity, must be systematically recorded and logged throughout the flight campaign [68].

Before data acquisition, the structure must be thermally activated, typically by increasing the internal temperature, to establish a measurable temperature gradient across the interior and exterior surfaces. This allows thermal bridges, missing or defective insulation, and other thermal anomalies to be detected [52].

Flight types from the methodology applied are as follows (Table 1):

Table 1. Technical requirements of UAV thermal flights. Data collection.

Flight	Vertical 	Oblique 	Horizontal 
Trajectory	 Grid	 Double Grid	 [69] Zig-zag Ring
Camera position	90°	30–45°	0–30°
Image Overlay (calculated with respect to the thermal camera GSD)	70–80%	70–80%	>80%

General (oblique): Taken 15–20 m above the top of the ceiling with the camera at 45°, flying zigzag paths outside the building boundaries [52] (Figure 3).



Figure 3. Data obtained from the thermal camera (**left**) and RGB camera (**right**) from the drone flyover performed on the Faculty of Psychology of the University of Warsaw Pilot construction site on 18 March 2025—view of the western façade [source: with the consent of Mostostal Warszawa SA].

Vertical roof: Completed 5–10 m away from the apex of the top of the highest portion of the roof with the camera at 90°, shooting all four corners in a zigzag order [67] (Figure 4).

Horizontal façades: Completed 5–10 m away from façades with the camera between 0° and 30° with a zigzag line in front of the building, ensuring a shot of each corner [67].

The image's superposition should be 70–80% for general and roof overhangs and over 80% for façade overhangs [52,67].

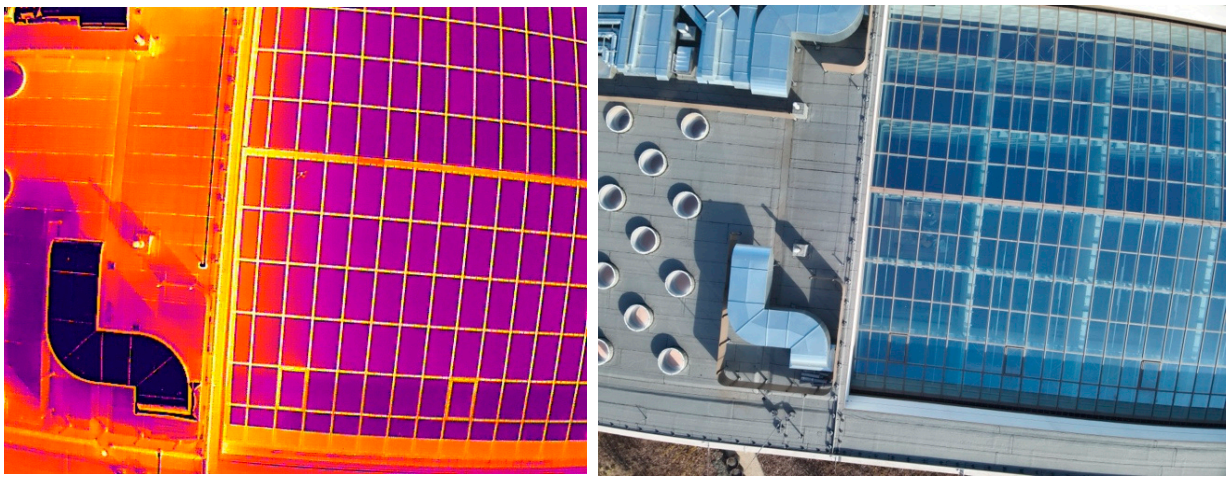


Figure 4. Data obtained from the thermal camera (**left**) and RGB camera (**right**) from the drone flyover performed on the Faculty of Psychology of the University of Warsaw Pilot construction site on 18 March 2025—view on the solar panel cells located on the roof [source: with the consent of Mostostal Warszawa S.A.].

3.1.4. Data Processing to Obtain Point Cloud and Thermal Representation of the Building

Explaining the data logged from the thermal sensors begins with processing the raw images obtained from the infrared camera. To that end, we utilized the open-source ImageJ software [70]. More precisely, we utilized the IRImage plugin [71], which allows the importation of thermal images in RAW or radiometric format and performs a precise conversion of the digital intensity (DN) values into absolute temperatures in degrees Celsius or Kelvin [72].

Thermal conversion was achieved by applying the default radiative transfer equations in thermography, taking into account fundamental parameters such as material emissivity, reflected temperature, and object distance. The IRImage plugin allows the manual input of these parameters or from inserted metadata. It offers the ability to calibrate images against known thermal reference points, thereby increasing measurement accuracy.

Following calibration and correction, the thermal images were combined with the RGB photogrammetric data within software developed by the Universidad Politécnica de Madrid, which is currently being refined. The software facilitates the multimodal fusion of information by implementing geometric registration algorithms to precisely register each thermal image with the three-dimensional model generated by Structure from Motion (SfM) from the RGB images. The result is a thermally enriched point cloud, where every point not only has spatial coordinates (X, Y, and Z) and color (R, G, and B), but also a temperature value associated with its position on the building envelope [73].

3.1.5. Platform for the Visualization of Thermal Bridges [74]

For the visualization of the point clouds as well as the thermal visualization of the buildings, Potree [75], the web-based point cloud viewer, which utilizes WebGL, was employed. Potree is an open-source viewer created primarily to be used with very dense datasets, most often generated via laser scanning or photogrammetry, including thermally enhanced 3D models obtained throughout the scope of this study. Its key advantage lies in its ability to display millions of points in real-time within the browser without any other

software, hence emerging as the ideal tool for presenting and interactively assessing digital building models. The point cloud representation is in Figure 5.

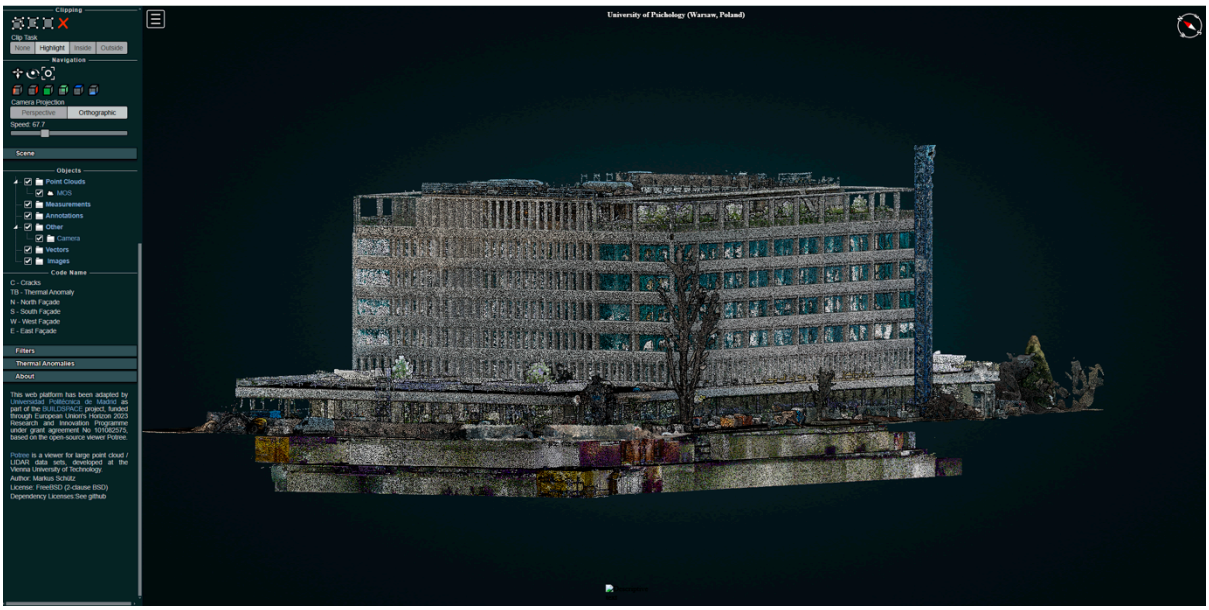


Figure 5. Point cloud of the Faculty of Psychology of the University of Warsaw Pilot visualized in the BUILDSPACE platform for Service 2 (the thermal representation to be overlayed on this point cloud) [source: with the consent of Mostostal Warszawa SA and Universidad Politécnica de Madrid].

Potree supports top-of-the-line spatial browsing and analysis functionality. Among them is thermal visualization, which allows the use of a continuous chromatic scale on the scalar values of all cloud points, and in this case, the temperature value. This enables the coldest or hottest areas of the building to be graphically displayed using the adjustable color map, so thermal anomalies, such as thermal bridges, humidity, or heat losses, can be easily identified. The user can adjust the color scale parameters to accommodate the specific case study thermal range.

One of the most valuable instruments within Potree's environment is the Point Tool, which allows you to inspect one point at a time from the cloud. If you click on a point, the viewer displays its spatial coordinates (X, Y, and Z) and associated metadata, including the temperature value in degrees Celsius, with decimal precision. This functionality is beneficial for performing quantitative analysis within specific areas of the model without the need to export data to third-party tools.

Further, Potree also offers a superior user experience through functionality such as orbital navigation, cross-section creation, clipping tools, and multi-layer visualization of various data layers (RGB, thermal, intensity, etc.). This allows one to visually examine the model from different angles, identify areas of interest, compare them, and conduct detailed studies that merge geometric and thermal data in an integrated fashion.

With these functionalities, Potree becomes a significant aid for the thermographic inspection of three-dimensional models. It offers an easy-to-use, multi-platform system designed for both professional technicians and end-users, with a focus on building energy diagnosis. Its use in this project enables one to correctly represent the thermal distribution on the real geometry of the building envelope, an indispensable step for energy efficiency diagnosis and rehabilitation intervention planning.

Figure 6 shows the temperature scalar field obtained by projecting infrared thermographic information onto the 3D point cloud reconstructed from UAV flights based on RGB images. The scene was rendered using Potree viewer, which enables user interaction with

the model, including dynamic temperature scale adjustment and access to individual point metadata, such as accurate temperature values. These scalar fields support the detection of thermal anomalies, including thermal bridges or insulation defects.

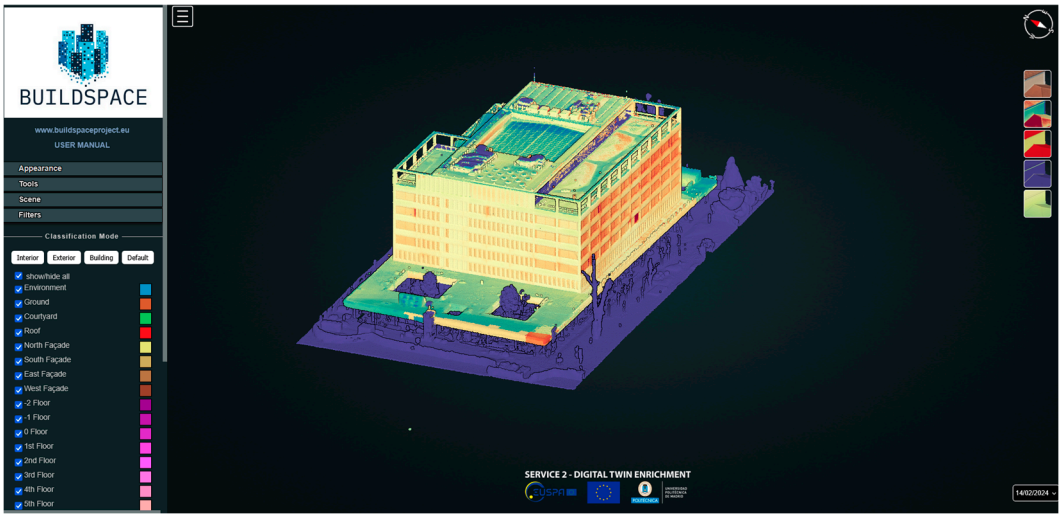


Figure 6. Thermography of the Faculty of Psychology of the University of Warsaw Pilot visualized in the BUILDSPACE platform for Service 2 [source: with the consent of Mostostal Warszawa SA and Universidad Politécnica de Madrid].

3.2. Thermal Calibration and Thermal-to-3D Integration Workflow

A two-point black-body calibration was performed before each flight. Laboratory-grade reference plates were stabilized at 25 °C (ambient) and 45 °C (hot), providing the anchor points for a linear radiometric correction in ImageJ (IRImage plug-in v 2.1.0). The camera emissivity was set to 0.95, while the reflected apparent temperature (Trefl) was measured on-site using a calibrated thermohygrometer and recorded in the metadata. Aggregating the residuals from three flights (n = 64 calibration frames) yielded a calibration uncertainty of ±1.8 °C at the 95% confidence level.

Surface-material emissivities were taken from recent façade surveys: 0.94 ± 0.02 for painted render, 0.91 ± 0.03 for clay brick, and 0.88 ± 0.03 for precast concrete. A first-order sensitivity test confirmed that a ±0.05 change in emissivity translates into a variation of <0.6 °C in apparent temperature over the 0–40 °C range, well below the anomaly thresholds used in this study.

The thermal-to-3D mapping comprised four sequential steps: (1) Radiometric orthorectification of the R-JPG frames was performed in ImageJ/IRImage to remove lens distortion and align each pixel with its corresponding georeferenced footprint. (2) Pixels belonging to zones with emissivity $\varepsilon < 0.85$ were automatically masked to avoid low-confidence readings. (3) The remaining pixels were projected onto the photogrammetric point cloud by a barycentric interpolation of the underlying mesh triangles, preserving sub-pixel positional accuracy. (4) For every resulting point, surface temperature statistics (mean and standard deviation) were aggregated at the IFC-element level and stored as custom properties (SurfaceTemperatureMean and SurfaceTemperatureSD). The processing scripts (Python 3.11, OpenCV 4.9, and Open3D 0.18) will be released as open-source once the project NDA expires (planned Q4 2025), enabling full reproducibility of the workflow.

3.3. Case Study 2: IFC 4.3 Class System—Information Content of the BIM Model in Low-Emission Construction

As mentioned earlier, from the perspective of the data flow between various stages of building construction, the information capacity of the BIM model and its elements plays a

significant role. The BIM model may be perceived as an aggregator of data provided that classification is standard for each construction process stage—from the conceptual model, through the model required for obtaining a building permit, construction model, workshop model (used for producing structural elements or determining assembly methods), as-built model (used for work settlement and formal acceptance of the building) to facility management model (serving for evacuation purposes and future demolition). It is only property sets and properties whose usage varies between those stages. Studying the structure of BIM data and its role in managing energy efficiency throughout the building's lifecycle as well as enriching the BIM model with drone flyover data information, it is essential that the information about properties of building elements affecting the energy efficiency of the building is included at the first stage of the construction process and then can be subjected to enrichment or reduction depending on the needs of a specific phase of the construction process.

The case study properties relevant to energy efficiency are based on one structural element, a wall (IfcWall), considering the IFC 4.3 class system. The open-access buildingSMART International bSDD service is used as the database of the class system and related properties and property sets.

3.3.1. IfcWall Information Content in Terms of Energy Efficiency

As the thermal information acquired from thermovision concerns the external walls of the building and the ceiling on which the solar panel cells are located, the possibility of mapping the temperature data obtained during the drone flight to the existing properties in IFC 4.3 will be analyzed below. It will be examined whether the IFC class system in this version, as represented in the bSDD dictionary, allows for a direct representation of this data or whether an additional property is necessary.

Considering IFC 4.3, external walls are represented by the IfcWall class or its subtype IfcWallStandardCase. The property set explicitly provided for the aforementioned class is Pset_WallCommon, which includes the property Thermal Transmittance that describes the heat transfer coefficient (U-value). However, when related to temperature, this property does not exactly refer to the data obtained from a thermal camera. Regarding temperature, within the property set Pset_Environmental Condition, three properties could be considered: Operational Temperature Range, Reference Environment Temperature, and storage temperature range. Nonetheless, the definition of the first one is 'The temperature range in which the device operates normally'. The definition of the second is 'Ideal temperature range' and the third refers to the 'Allowed storage temperature range that the element complies with'. In conclusion, neither of them provides space for mapping the thermography value. Other parameters in this property set pertain to a different range, not temperature. Similarly, it is the same in the other two property sets that could be regarded as possessing the appropriate properties: Pset_Environmental ImpactIndicators and Pset_Environmental ImpactValues. (bSDD Search). They both present the broad scope of environmental aspects, but do not address temperature. In conclusion, in the latest IFC class system version 4.3, there are no properties related to the wall surface temperature that could represent values obtained from thermography.

While the current IFC schema lacks properties dedicated to thermal inspection data, the existing openBIM frameworks could potentially support such integration. In particular, the COBie format could be extended by including custom parameters, mentioned above, related to surface temperature or thermal anomalies in its component schedules. Furthermore, the development of a dedicated Model View Definition (MVD), such as a 'Thermal Analysis View', would allow for standardized extraction and exchange of relevant IFC properties

related to thermographic data. Nevertheless, such properties should first be defined within the IFC model.

While enriching the BIM geometry representation with thermography data is feasible in native models, it would be valuable if this could also be possible in the openBIM format, specifically in its information layer, which is IFC. Taking the IFC class system as a complex example, extending IFC 4.3 by introducing a new property is recommended, and the proposition will be presented below.

To enrich the IFC 4.3 schema, which currently lacks a default property for wall surface temperature, where temperatures from thermography could be mapped, two approaches can be pursued (Figure 7). In the first one, a new property named 'WallThermalImaging' could be introduced in the property set Pset_WallCommon. This would be the property with the definition 'Wall surface temperature obtained from thermographic surveys' and the unit of Celsius degrees [°C], data type: real. The second proposed approach would be based on the creation of a new specific property set named 'Pset_Surface Temperature', which could include three properties: the first—'SurfaceTemperatureExternal' with the definition of 'External wall surface temperature obtained from thermographic surveys'; the second—'SurfaceTemperatureInternal' defined as 'Internal wall surface temperature obtained from thermographic surveys'; and the third—'ThermalAnomalyIndicator' with the definition 'A logical value indicating the presence or absence of thermal anomalies based on thermographic data'. The data type of the first two properties would be 'Real' and the 'Boolean' for the third. The Boolean value will simultaneously serve as an adequate representation for indicating heat transfer issues, such as thermal bridging. With such approaches, IFC 4.3 would have the potential to support better integration of BIM and data from thermographic surveys, including both drone flyovers and manual inspections. Therefore, it would provide more comprehensive support for thermal building analysis and construction efficiency, offering a familiar environment for storing various data types, including thermal imaging data.

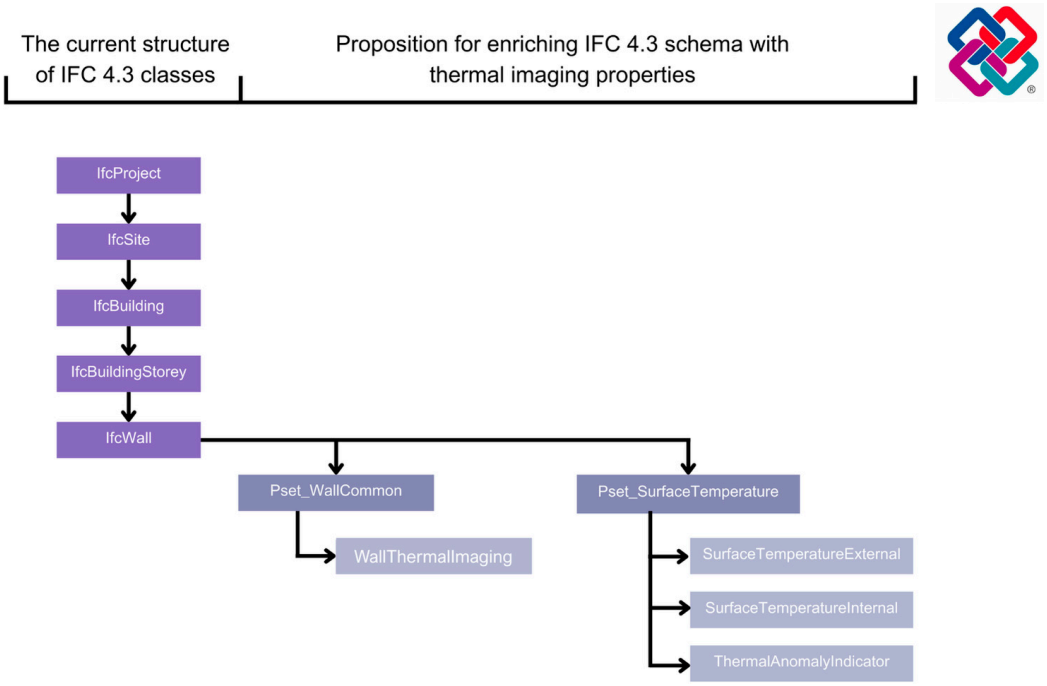


Figure 7. Proposition for enriching the IFC 4.3 schema with thermal imaging properties [source: authors' own elaboration].

The possible approach could also include creating a custom classification containing one of the aforementioned property sets and corresponding properties. By publishing the

classification in the buildingSMART Data Dictionary service, the dictionary would become public, enabling its widespread use. As the concept of the bSDD service is the creation of a shared dictionary that users can enrich with classes, properties, and property sets created by themselves and mapped to IFC entities and properties when possible—without duplicating those already existing—provided that there are currently no adequate properties for representing thermal imaging data, this approach can be considered appropriate and correct.

The dictionary above was created using usBIM.bSDDeditor from ACCA (Figure 6). A sample class, Wall, corresponding to the IfcWall class, was created along with properties corresponding to those proposed in Figure 8: 'Surface Temperature External' (data type: Real), 'Surface Temperature Internal' (data type: Real), and 'Thermal Anomaly Indicator' (data type: Boolean). In the next step, they were grouped into the Property Set 'SurfaceTemperature'. The bSDD dictionary was then downloaded in .json format, validated, and uploaded to the bSDD service through the manage.bsdd.buildingsmart.org page (Figure 9).

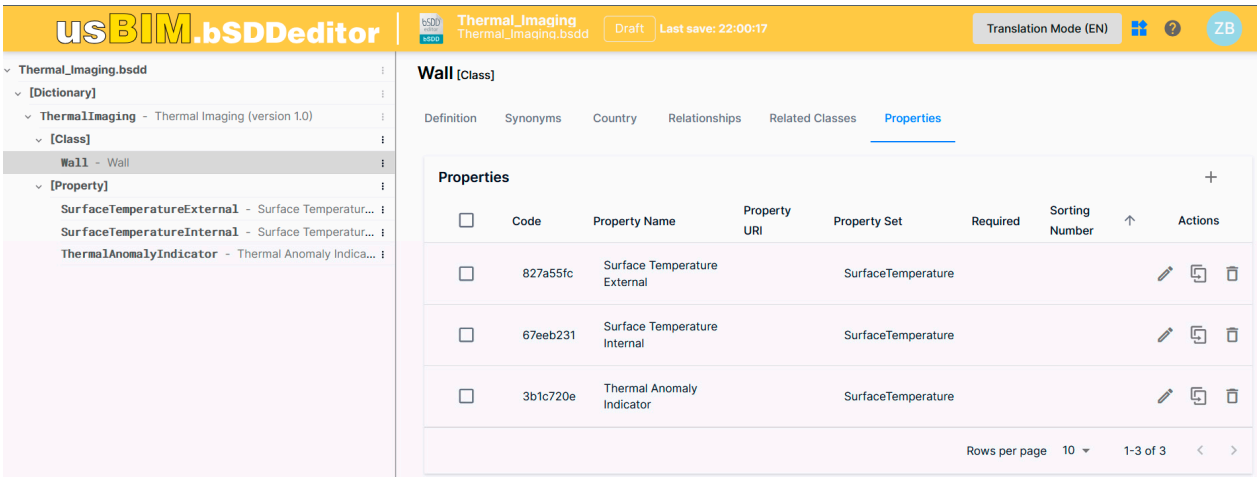


Figure 8. bSDD dictionary prepared in the usBIM.bSDDeditor from the ACCA software [source: authors' own elaboration].

Since the IFC (Industry Foundation Classes) format enables openBIM interoperability throughout the project lifecycle [76], it was considered necessary that data obtained from thermographic analysis could be directly integrated at the IFC model level, bypassing the native model. Therefore, as a further step, the possibility of applying this dictionary was demonstrated in Blender, which, thanks to the Bonsai plugin, enables direct connection to the bSDD service and assignment of a class with its associated properties directly within the Blender environment (Figure 9). For this purpose, a representative wall was selected and linked to the 'Wall' class from the 'ThermalImaging' bSDD dictionary (bSDD Search). Properties related to this class were automatically displayed in Blender, enabling the entry of property values (for 'Surface Temperature External' and 'Surface Temperature Internal') and marking the Boolean 'Thermal Anomaly Indicator'. As in the project, only the external temperature was taken into consideration. The first property was filled in with the value obtained during the thermographic inspection, as shown in the thermal image presented in Figure 10. As this value does not indicate a thermal anomaly for the concrete wall, the 'Thermal Anomaly Indicator' was not marked. At this stage, the property concerning the internal surface temperature of the wall was omitted, with no value entered.

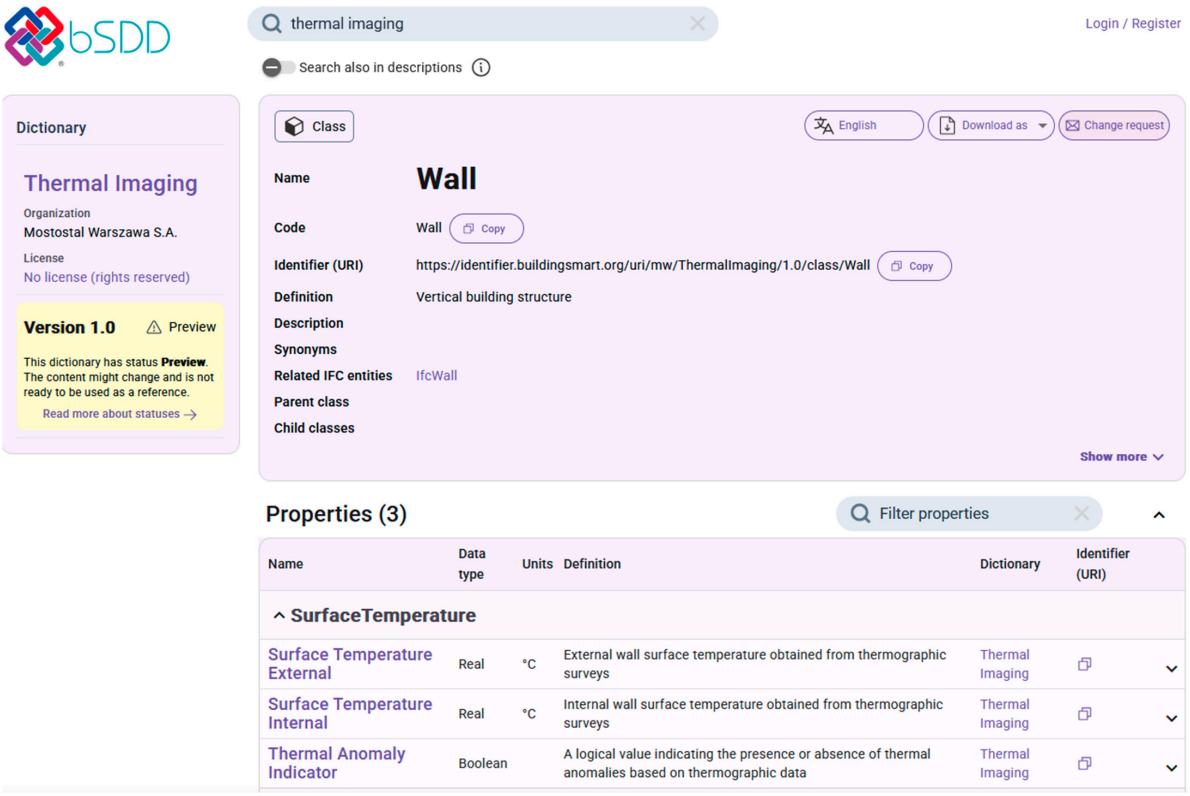


Figure 9. bSDD dictionary successfully published in the bSDDservice. [source: authors' own elaboration].

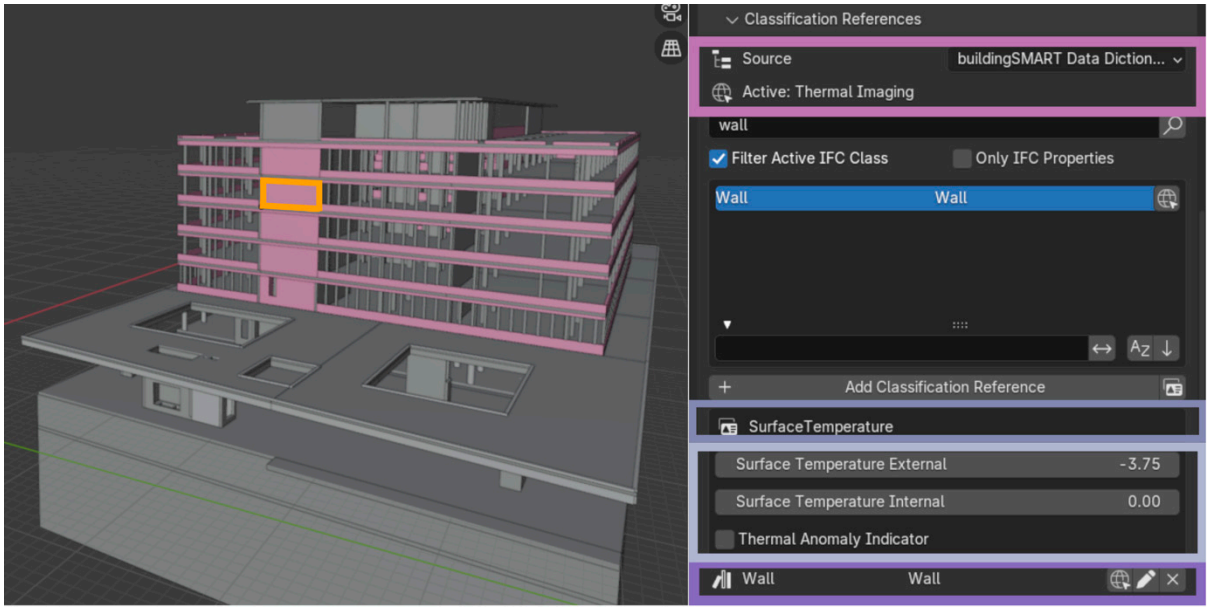


Figure 10. Class and corresponding properties—as defined in bSDD—applied to the selected wall in the Blender environment [source: authors' elaboration with the consent of Mostostal Warszawa SA].

At this stage of the work, the process of assigning thermal values is manual, although there is potential for algorithmic automation that would enable a smooth transition to openBIM thermography.

An alternative approach to the one proposed here does not involve extending the IFC 4.3 structure or developing a custom classification based on the bSDD dictionary. Instead, it relies on defining and assigning parameters directly within the native software

environment for each specific project. In this scenario, classifications and parameters such as 'Surface Temperature External', 'Surface Temperature Internal', or 'Thermal Anomaly Indicator' must be manually created for each BIM model. A key challenge of this approach lies in the exchange of such classification files between project stakeholders (e.g., investors, contractors, and subcontractors), as native files are significantly larger than IFC files. Furthermore, each party must have access to potentially expensive software that supports the specific native file format, whereas IFC viewers are typically free. Additionally, the operation of native authoring tools is often far more complex compared to the more intuitive IFC viewers. These considerations suggest that extending the IFC 4.3 schema or developing a BSDD-based dictionary, which can be effortlessly imported into different projects (BIM models), represents a more interoperable and open-standards-based approach.

3.3.2. Justification for Custom bSDD Terminology and Compatibility with Standards

To address the lack of predefined properties for thermographic data within IFC 4.3, a custom bSDD dictionary was developed following the official buildingSMART methodology. The introduced properties (e.g., SurfaceTemperatureExternal and ThermalAnomalyIndicator) are explicitly mapped to IFC classes (e.g., IfcWall), ensuring semantic alignment and future interoperability. The approach is not intended to replace the existing standards but to extend the current IFC schema, which presently does not support surface temperature representation or anomaly flags. The creation of custom property sets is explicitly allowed and encouraged by the bSDD platform to facilitate open data sharing until such extensions are formally incorporated into IFC releases. By publishing the dictionary through the official bSDD service, it is made publicly accessible and reusable, promoting standardization across projects. Future efforts may include submitting these properties for formal review by buildingSMART International as part of ongoing schema development processes.

4. Results

The presented study demonstrated the practical feasibility and benefits of integrating drone-acquired thermal imaging data into BIM models to support energy efficiency analysis across a building's lifecycle. When combined with BIM and digital twin technologies, UAV-based thermographic surveys enable more precise localization and quantification of thermal anomalies, significantly improving the early detection of thermal bridges and insulation defects.

The BUILDSPACE project pilot implementation (case study 1) validated that coupling photogrammetric and thermal data collection methods with digital twin enrichment can generate actionable insights into a building's energy performance, even during the construction phase. Moreover, the ability to visualize temperature data in a 3D environment, using platforms such as Potree, enhances accessibility and usability for stakeholders. The temperature-enriched 3D model allows for the interactive exploration of thermal values directly within the point cloud without the need to export data to external software. However, the lack of standardized methods for storing such data in open BIM formats, such as IFC, limits broader adoption.

Case study 2 articulated that IFC 4.3 currently lacks native properties for storing thermographic inspection data. A proposed solution involved extending the IFC schema by defining new properties such as 'Surface Temperature External', 'Surface Temperature Internal', and 'Thermal Anomaly Indicator'. The study showed that these could also be implemented in a custom bSDD property set and integrated into an openBIM workflow using tools like Blender and the Bonsai plugin. This enables structured, interoperable data sharing across various projects and stakeholders, making the storage of not only visual but

also informational-layer thermography and thermal anomaly data in the IFC-format BIM model intuitive.

A total of twelve thermal anomalies were identified across the building envelope, including elevated heat signatures at window junctions, parapets, and mechanical rooftop penetrations. Surface temperature deviations ranged from 3.1 °C to 5.6 °C above adjacent wall areas. These deviations indicate potential insulation discontinuities or thermal bridges. The anomalies were manually mapped to IFC elements using the bSDD schema in Blender.

5. Discussion

As proved in case studies, digital tools present innovative opportunities for enhancing building energy efficiency. However, challenges remain. Limitations related to data standardization, particularly in integrating thermal imaging outputs into openBIM environments like IFC 4.3, were observed. Although the manual extension of IFC schemas was proposed, a standardized, internationally recognized approach for incorporating thermography-based data into BIM models is still lacking. In addition, the acquisition of thermal data via UAVs is sensitive to environmental conditions and requires careful planning and calibration to maintain data quality.

Environmental conditions play a crucial role in the accuracy of UAV-based thermal imaging. Seasonal variations influence the temperature differential between interior and exterior surfaces, which is critical for anomaly detection. For instance, winter campaigns tend to yield more pronounced thermal contrasts due to higher indoor–outdoor gradients, while summer campaigns require night-time flights to avoid solar gains. Similarly, diurnal cycles and direct solar radiation can distort thermal readings by introducing surface overheating or shadows. These phenomena necessitate carefully planned flight windows and calibration strategies. Although this study does not explore these factors in depth, they are essential for practitioners aiming to optimize data quality in real-world inspections.

The analysis further highlighted that advances in machine learning and semantic segmentation offer opportunities for automating the mapping of thermal anomalies into building information modeling (BIM) elements, thereby reducing human input and increasing diagnostic precision. Nonetheless, more research is required to ensure robust and scalable deployment of such AI-enhanced methodologies.

Overall, the combined use of UAV, thermography, BIM, and digital twin technologies forms a promising pathway for improving building energy diagnostics and supporting the broader goals of sustainable, low-emission construction.

While the current research focuses on integrating UAV and thermography data into BIM using open standards, the application of AI/ML methods represents a natural and auspicious next step. Future development could involve the deployment of CNN architectures, such as Mask R-CNN or U-Net, to automate the identification of thermal bridges or insulation defects from raw thermographic images. Integrating these outputs with IFC-based BIM models can be achieved by linking segmented anomalies to IFC entities, thereby enriching the model's semantic layer. Such methods, if trained on annotated thermal datasets and validated on case studies like those described here, could significantly reduce manual labor and improve accuracy in large-scale audits.

5.1. Study Limitations

While integrating UAV-based thermography and BIM presents a promising approach to building energy efficiency analysis, several limitations must be acknowledged. Thermal data acquisition using UAVs remains highly dependent on environmental conditions. Wind, sunlight, and temperature gradients significantly influence the quality and reliability of thermal imaging. Consequently, data collection campaigns are restricted to specific

weather windows, limiting flexibility and scalability. Although technically feasible, integrating thermographic data into BIM models currently lacks standardization within openBIM frameworks. The proposed extension of the IFC 4.3 schema represents a preliminary solution; however, it requires broader validation and industry acceptance to ensure interoperability across platforms. The processing and enrichment of BIM models with thermal data are not fully automated. Manual calibration, thermal interpretation, and point cloud registration introduce subjectivity and the potential for human error. Robust, AI-driven workflows are needed to minimize manual interventions. The practical deployment of integrated UAV-BIM-thermography solutions requires specialized technical skills and equipment. This may hinder widespread adoption, particularly among smaller construction companies or facility managers with limited resources.

Moreover, while the methodology is scalable in principle, it is important to indicate potential cost-related constraints. UAV equipment can be expensive, and drone operations require certified pilots with appropriate licensing. Nonetheless, short-term drone rental services or commissioning a drone inspection from specialized service providers are available, offering a more affordable alternative. Regarding the BIM software, both the platform used in case study 1—developed within the BUILDSPACE project—and the tools applied in case study 2 were based on the IFC format and bSDD service and relied on open-source solutions, supporting easier and wider adoption. Labor and time requirements, particularly for manual data processing and interpretation, also remain a limitation. Addressing these through greater automation could improve efficiency and lower barriers to broader implementation.

5.2. Proposed Conceptual Framework for Algorithmic Thermal-to-BIM Mapping

While the current case study 2 demonstrates the feasibility of manually assigning thermal data to BIM elements in the IFC format, the scalability of this approach for large-scale implementation could limited. To address this challenge and support future automation, a conceptual framework for algorithmic mapping of thermal data to BIM elements is proposed. The framework includes the following core components:

- BIM element segmentation: The geometry of BIM elements (e.g., IfcWall, IfcRoof, and IfcWindow) would be extracted from the IFC model. Spatial matching techniques—such as bounding box intersection or proximity-based nearest surface detection—could be used to associate each region of the thermal point cloud with specific BIM elements.
- Temperature aggregation and analysis: For each matched BIM element, basic thermal statistics would be calculated using the corresponding subset of thermal data points. These aggregated values would serve as representative indicators of surface temperature for each element.
- IFC model algorithmic enrichment with thermal properties: Based on detection results, elements would be tagged with a 'ThermalAnomalyIndicator' property indicating the presence of potential insulation defects or thermal bridges. Newly computed temperature values and anomaly indicators would be appended to BIM elements as properties automatically through algorithmic integration with the IFC software API and bSDD service API.

Although this conceptual framework has not yet been implemented in the current study, it represents a logical continuation of the research and addresses the need for increased automation, particularly in large-scale thermal diagnostics and digital twin enrichment.

5.3. Influence of Seasonal and Diurnal Weather Factors

Thermal anomaly detection relies on the temperature contrast between the building envelope and the surrounding air. In mid-latitude climates, this contrast is naturally highest on clear winter mornings and lowest on summer afternoons. Experience from our pilot flights and published benchmarks indicates that a ΔT of at least 8–10 °C is desirable to keep segmentation accuracy above practical thresholds. When daytime ΔT falls below this level, the apparent temperatures begin to cluster within the sensor's NETD, increasing the risk of false negatives.

Short-wave solar irradiation is an equally important source of bias: sunlit façades may display local 'hot spots' unrelated to thermal bridges. To minimize this effect, we recommend scheduling surveys within the first two hours after local sunrise or under uniformly overcast skies (global irradiance typically <100 W m^{-2}). If mid-morning flights are unavoidable, south- and west-facing façades should be captured last, after direct illumination has ceased.

Diurnal temperature cycles can also be exploited when winter campaigns are impractical, for example, during summer retrofit inspections. Evening flights—conducted once façades have cooled but the air temperature remains relatively high—often restore a usable ΔT without the need for seasonal waiting. In very stable climatic zones, practitioners can refer to local meteorological forecasts to identify nights with ample nocturnal cooling and plan dawn missions accordingly.

Taken together, these observations suggest a simple operational rule set: (i) target survey windows that deliver $\Delta T \geq 8$ °C, (ii) avoid or mask sun-lit surfaces, and (iii) prioritize dawn or dusk slots whenever possible. Adhering to these guidelines significantly improves data reliability while maintaining acquisition logistics that are compatible with typical construction-site constraints.

5.4. Quantitative Accuracy of Anomaly Detection

Thermal bridge detection performance: An interim evaluation against expert-drawn reference masks (12 façade anomalies, ~46,000 labeled pixels) shows that the workflow achieves a precision of 0.85–0.89, a recall of 0.80–0.88, and an F1-score of 0.83–0.89. These ranges are based on three flights conducted under comparable dawn conditions, indicating that fewer than one in five detected pixels are false alarms and that more than four out of five true anomaly pixels are correctly identified. Although the full project-wide validation will only be possible after the final measurement campaign, these preliminary figures confirm that the proposed method already meets the commonly accepted threshold ($F1 \geq 0.80$) for façade-scale diagnostics.

6. Conclusions

This study explored the integration of drone-acquired thermal imaging data into BIM-based workflows to enhance building energy efficiency analysis. The findings demonstrated that combining UAV thermography, photogrammetric modeling, and BIM enrichment enables the early-stage identification of thermal inefficiencies, supporting more informed decision-making throughout the building lifecycle.

The case study from the BUILDSPACE project showed that enriching digital twin models with multimodal data increases the transparency and precision of energy performance evaluations. Proposed enhancements to the IFC 4.3 schema, including additional properties dedicated to thermal imaging, also point to a potential direction for developing more comprehensive openBIM standards. However, the practical application of these methodologies revealed challenges related to environmental conditions during data acquisition and the need for more structured approaches to data integration. Future work should

focus on developing automated workflows for thermal data processing and promoting standardization for integrating thermal properties into openBIM models. Integrating UAV, BIM, thermography, and AI technologies is a promising direction for advancing sustainable construction, supporting the design, assessment, and maintenance of energy-efficient and resilient buildings.

Although not implemented in this study, the potential for incorporating AI-based thermal analysis was highlighted. Future research should explore the training and deployment of segmentation and prediction models for automating anomaly detection, which would further strengthen the BIM-based energy diagnostics workflow.

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