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A Digital Twin Approach Integrating IoT and AI for Monitoring and Assessing Roof Degradation in Historic Buildings

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Abstract

The EN-HERITAGE project aims to define and prototype an integrated digital platform for the management of virtual models of buildings belonging to the historic built heritage, with a particular focus on slate roofing systems. The platform integrates IoT technologies for environmental monitoring, architectural surveys carried out using laser scanning and photogrammetry, HBIM models, and artificial intelligence algorithms for the analysis of degradation phenomena. The pilot application was conducted on the *Albergo dei Poveri* complex in Genoa, providing a replicable methodology for the planned conservation of the historic built environment. Preliminary results highlight the effectiveness of the platform in integrating heterogeneous data, providing stakeholders involved in the management of extensive architectural heritage with concrete support for decision-making processes and greater efficiency in planning maintenance and restoration interventions on historic buildings.

Keywords: cultural heritage; digital twin; IoT environmental monitoring; integrated survey methodologies; AI technology

1. Introduction

1.1. Application Context

The research is set within the context of the conservation of the historic built heritage, a field in which managing authorities are required to coordinate a wide range of buildings of considerable complexity, often characterized by incomplete documentation and limited knowledge of their conservation state. The difficulty in correlating environmental data, surveys, and direct observations restricts the possibility of implementing an efficient planning of maintenance and restoration activities based on updated and verifiable information.

In every restoration project, it is essential to assess the conservation conditions of materials and construction elements: the identification of phenomena and their quantification constitute a fundamental phase of the knowledge process. This analysis concerns not only the definition of degradation forms but also the identification of the relationships

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between materials, environmental conditions, and external factors that influence their origin and development.

Within this framework, particular attention is given to roof systems, which are especially exposed to external agents and often difficult to diagnose due to limited accessibility, yet crucial in the overall conservation of a building.

1.2. Objectives of the "EN HERITAGE" Project

The EN-HERITAGE project was developed to create an integrated platform supporting the management, diagnostic assessment, and conservation of Genoa's historic built heritage. It is based on a multidisciplinary approach aimed at collecting, processing, and sharing architectural, energy, and environmental data.

The solution involves the use of interoperable digital tools for the monitoring and diagnosis of the state of conservation, with the goal of supporting a more efficient and predictive management of historic buildings.

One of the main objectives is the automatic mapping of degradation phenomena affecting Genoa's historic roofs, through a machine learning model trained on multi-source datasets.

The decay maps produced by the system are interactive and can be validated by expert operators via a dedicated interface, facilitating the continuous updating of diagnostic information and the planning of scheduled conservation interventions by the authorities responsible for heritage protection.

1.3. State of the Art

1.3.1. Application Scenario

The conservation of historical architectural heritage is strongly influenced by atmospheric agents and pollutants, which contribute to the onset and progression of degradation phenomena. To address these critical issues, several European and national initiatives promote the adoption of advanced digital technologies for monitoring, documenting, and preserving the built heritage. Among these, the European Cultural Heritage Cloud [1] and the National Plan for the Digitization of Cultural Heritage [2] represent long-term strategies aimed at promoting data sharing and the adoption of interoperable digital solutions in the management of historical architectural heritage. Another indicator of the strategic importance attached to the preservation of cultural heritage in Europe is the European Heritage Days [3], which, through their annual program, encourage dialogue between institutions and stakeholders on the social, political and economic challenges facing the sector, while raising awareness among policymakers and citizens of the need to protect it. At the local level, the issue of conservation has also gained importance. In the context of the city of Genoa, the preservation of the historic built heritage is supported by several institutional initiatives that have introduced digital tools and environmental monitoring systems. The Management Plan of the UNESCO site "*Le Strade Nuove e il Sistema dei Palazzi dei Rolli*" defines, for instance, operational strategies for conservation and for the control of risk factors affecting historic buildings [4]. As part of the Genoa 2050 Action Plan, the Municipality of Genoa has developed strategies in line with the Sustainable Development Goals, focusing on protecting the city's UNESCO heritage from environmental impacts and climate change. The *UNESCO Sentinel initiative* involves the development of an integrated monitoring system based on satellite mapping, proximity sensors and an interoperable dashboard (*BIG-EYE objective*, pp. 22–25) [5], aimed at assessing the effects of air pollution and climate change on the city's historic fabric.

In addition, the urban policies outlined in the Genoa 2050 Action Plan [5] include measures aimed at the digitalization of heritage management, the use of sensors and integrated platforms, and the enhancement of the climate resilience of the historic built fabric. This set of initiatives demonstrates how the city is already engaged in activities consistent with the objectives of the EN-HERITAGE project, providing an advanced local context for the development of integrated methodologies for diagnosis and conservation.

1.3.2. In Situ and Remote Environmental Monitoring Technologies

In this field of application, the study and analysis of atmospheric pollutants, in relation to their presence and concentration, must be carried out with a predictive approach, as these factors significantly influence the assessment of a building's state of conservation.

Monitoring the most impactful environmental variables is essential to verify the stability of parameters within safe thresholds, with the aim of preventing potentially harmful levels for materials and, consequently, avoiding the onset or progression of degradation phenomena. Atmospheric pollution monitoring is typically performed through fixed monitoring stations equipped with automatic analyzers for the continuous measurement of the main pollutant species and associated meteorological parameters [6].

In support of traditional methods, recent years have seen the introduction of IoT (Internet of Things) systems, consisting of multiparametric stations for measuring meteorological variables (temperature and relative humidity) and the concentration of major atmospheric pollutants (SO, SO_2, NO, NO_2, O_3, $PM_{2.5}$, and PM_{10}) (Table 1).

Table 1. Overview of the IoT technologies and the corresponding IoT technologies.

IoT Technology	Environmental Parameters
Bettair static node	CO, CO_2, H_2S, NO_2, NO, O_3, PM_{10}, PM_1, $PM_{2.5}$, SO_2, pressure, relative humidity, temperature
Smart Rainfall System	Rainfall intensity

These devices, characterized by compact dimensions and autonomous operation, enable remote access to configuration, diagnostics, calibration, and automatic data export through Internet connectivity and the use of cellular networks for data transmission.

Data processing is carried out using artificial intelligence algorithms, particularly machine learning techniques, which learn to recognize recurring patterns during the training phase [7].

Remote monitoring through satellite platforms such as Copernicus and Landsat provides extensive territorial coverage for environmental parameters such as surface temperature, atmospheric humidity, and pollutant concentrations.

Satellite data offer variable spatial resolution and regular temporal frequency, enabling multiscale analyses ranging from regional contexts to local detail.

The integration of in situ data, satellite observations, and climate reanalysis datasets represents the most effective approach for a comprehensive understanding of degradation processes, supporting historical analyses, the validation of predictive models, and the planning of conservation interventions based on quantitative evidence [8].

1.3.3. Existing Technologies for Architectural Survey and Thermographic Inference

The survey phase represents a fundamental step in the process of acquiring architectural space, during which, in addition to the recording of geometric data, the objectives of the activity, the representation scales, the required level of detail and accuracy, as well as the type and configuration of the instruments to be employed, are defined.

The use of advanced surveying technologies for digital data acquisition has introduced new methodologies and operational protocols for the representation of the built environment. It is essential to balance data accuracy with the complexity of data management, according to the intended purpose and processing requirements. Several studies have defined different levels of survey accuracy based on the specific applications of the data, such as analyses of the building's state of conservation, support for structural assessments, monitoring activities, and energy evaluations [9].

The two main technologies for three-dimensional metric surveying today are Terrestrial Laser Scanning (TLS) and Structure from Motion (SfM) photogrammetry.

TLS, based on the measurement of the laser beam's time of flight, generates high-density point clouds with millimetric accuracy, enabling a detailed representation even of complex geometries. The acquired points include attributes such as intensity, color, and reflectance, which are useful for geometric, material, and monitoring analyses.

Derived techniques, such as airborne LiDAR, extend data acquisition to a territorial scale, providing lower resolution but greater spatial coverage in reduced time, making them ideal for morphometric analyses and studies on terrain morphology.

In parallel, SfM-MVS photogrammetry, based on the automatic correlation of images acquired by UAVs, enables the generation of dense and georeferenced 3D models with high spatial resolution (GSD—Ground Sampling Distance).

The integration of drones into architectural surveying has made it possible to achieve rapid documentation with high operational flexibility, even in complex or difficult-to-access environments. Some activities involve the planning of flight paths and the definition of technical parameters according to the survey objectives, ensuring consistency between the acquisition methods and the required level of accuracy [10,11].

In recent years, there has been a growing awareness of the importance of integrating photogrammetric (image-based) and laser scanning (range-based) technologies in the processes of analysis and understanding of cultural heritage, both for their combined use [12] and for a critical comparison of their respective results [13].

An additional contribution is provided by thermographic surveys, which add a diagnostic layer based on the thermal response of materials, useful for detecting detachments, moisture, or structural anomalies not visible under natural light.

1.3.4. Analysis of Material Degradation Processes

Attention to the genesis and development of degradation phenomena emerged as one of the consequences of the changing attitude towards historic architecture that took shape between the eighteenth and nineteenth centuries. Previously, interventions on historic buildings generally involved the replacement of deteriorated elements or the demolition and reconstruction of compromised parts. With the growing awareness of the need to preserve the monument in its material integrity and to ensure its transmission to future generations, the necessity arose to investigate the factors of deterioration in order to strengthen both preventive and protective measures, aimed at containing or at least slowing down the processes of decay.

The study of the genesis and development of degradation phenomena has been structured into different but interrelated fields: the diagnostic field, which developed from the 1930s onwards with the introduction of scientific methodologies applied to material conservation and the progressive rationalization and parametrization of the causes and effects of decay [14]; the physico-chemical field, focused on analyzing the processes of interaction between constituent materials and their environment [15]; the biological-chemical field, dedicated to the identification and study of biodeteriogenic agents responsible for biotic alteration processes [16]; and finally the regulatory field, aimed at defining shared terminologies and standardized procedures for the description and assessment of degradation phenomena [17,18].

These fields are today complemented by more recent lines of research, including the application of non-invasive diagnostic techniques and advanced sensor-based monitoring systems, designed for real-time collection of microclimatic data and for the predictive evaluation of the conservation state of materials [19].

1.3.5. Existing Technologies for the Integration and Visualization of Architectural Data and Building Degradation Information

In recent years, the representation of architectural information, together with data related to the conservation state of buildings, has evolved through the introduction of new digital protocols and methodologies. Building Information Modeling (BIM) has introduced an innovative approach to data management, enabling the association of semantic information with building components and allowing information models to be queried, updated, and made interoperable [20,21]. However, the management of heterogeneous data, the continuous updating of information, and the representation of complex geometries have highlighted the limitations of HBIM (Heritage Building Information Modeling), particularly regarding the integrated management of the information model.

1.3.6. IOT and AI Systems

The technological evolution in the field of cultural heritage conservation has led to the synergistic integration of IoT systems and artificial intelligence for the monitoring and predictive management of degradation phenomena. Smart IoT sensors are advanced devices capable of detecting environmental parameters with high precision and transmitting data in real time to centralized analytical platforms. They are characterized by compact dimensions, autonomous operation, and connectivity through cellular networks that enable remote access. When applied to data acquired through surveying technologies, artificial intelligence can transform large volumes of information into interpretable models using machine learning algorithms. Convolutional neural networks (CNNs) enable the automatic segmentation of surfaces, distinguishing between different forms of surface decay and structural anomalies. Gradient boosting algorithms (such as XGBoost and CatBoost) effectively process structured tabular data, capturing complex nonlinear relationships between environmental variables and degradation phenomena [22].

Temporal comparative analysis based on machine learning makes it possible to trace the origin and evolution of degradation phenomena by comparing models acquired at different time intervals. This approach supports predictive simulations of future effects and the planning of proactive interventions grounded in analytical data [23].

2. Materials and Methods

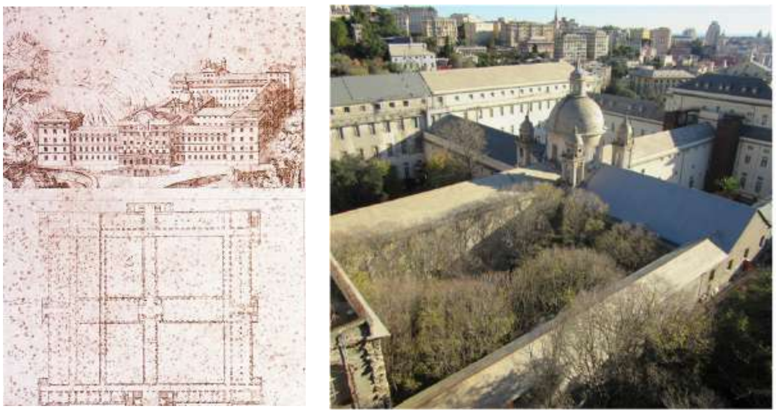
The experimental methodology of the EN-HERITAGE project, applied to a real case study, is aimed at validating a digital system capable of integrating surveying, environmental monitoring, and information modeling and management processes.

The adopted approach allows for the analysis and correlation of heterogeneous datasets, supporting decision-making processes oriented toward the planned conservation of historic architectural heritage. In particular, the experimental activity focuses on roof structures, an area where degradation phenomena are typically more pronounced due to exposure to atmospheric agents, limited accessibility, and the complexity of maintenance operations.

2.1. The Case Study

A comprehensive analysis of potential case studies within the UNESCO sites of Genoa led to the selection of the *Albergo dei Poveri* complex for the experimental phase of the research. The choice is motivated by the presence of slate-covered roofs, which show a variety of surface degradation phenomena, accentuated by direct exposure to atmospheric agents. In addition, the site offers favorable conditions for the integrated execution of aerial surveys with drones with ground support based on laser scanner technology, used for georeferencing, and aligning the acquired data.

The complex, founded in 1656 by Emanuele Brignole as a welfare institution, has a square layout with a central Greek cross-shaped core, occupied by a church, two oratories and an infirmary, which divides the central space into four independent courts (Figure 1). After its original function ceased in the 20th century, the University of Genoa obtained a concession from the Brignole Foundation and in 2003 began its restoration and adaptation into a university campus. However, many parts that have not yet been restored show serious signs of deterioration that require targeted conservation work. Specifically, the slate roofing, currently in a condition of poor conservation, shows localized gaps, spalling and exfoliation of the slates, and widespread alterations due to coherent and incoherent deposits and biological patina.



(**a**) (**b**)

Figure 1. *Albergo dei Poveri* complex (Genoa): (**a**) historic floor plan and axonometric by an anonymous author, 1835; (**b**) detailed photo of the roofing system.

2.2. Environmental Monitoring Phase

Environmental monitoring is one of the central components of the EN-HERITAGE project, as it provides the knowledge base for analyzing the processes of interaction between materials and the environment. The activity focused on the collection, processing and correlation of microclimatic parameters and atmospheric pollutant concentrations (black carbon, SO_2, NO_2, O_3), through the integration of in situ measurements and remote observations.

The measurement of Iic Black Carbon concentration at the monitoring site was performed using the Dadolab Giano BC1 [24]. It is a sequential PM_x sampler integrated with an optical module that continuously monitors Black Carbon (BC) concentration directly on the filter during sampling. The sampling sequence alternates blank and exposed filters (up to 21 positions) while a fixed-wavelength light source (λ = 635 nm) illuminates the newly exposed filter surface upstream of the deposition zone. A photodiode measures the light back-scattered or reflected at a fixed angle ($\approx$125° relative to the incident beam) from the particle-loaded filter. The raw voltage signal is converted via a calibration curve (polynomial in the form $ABS = A \cdot RFN^2 + B \cdot RFN$) linking the reflectance (RFN) to absorbance (ABS), through a patented technology (co-owned by Dadolab Srl and PM_TEN Srl). Once absorbance is known, the mass concentration of BC is calculated by applying a site-specific mass absorption coefficient (MAC) to the layer of particles on the filter; i.e., $BC = ABS \times MAC$. Importantly, the optical module is placed "on the fly" in the sampler inlet so that the aerosol flow and filter loading remain unchanged; thus, the filter remains available for subsequent gravimetric PM analysis or thermo-optical EC/OC characterization. This procedure offered real-time (or near-real-time) data on BC during sampling, integrated in a PM sequential sampler, enabling simultaneous PM and BC monitoring using a single instrument.

For air pollutants—such as nitrogen oxides (NO_x), sulphur oxides (SO_x), carbon dioxide (CO_2) and particulate matter (PM2.5 and PM10)—reference is made to remote monitoring techniques such as the Copernicus Atmosphere Monitoring Service (CAMS), which provides reanalysis datasets capable of estimating average annual concentrations, which are essential for assessing air quality and monitoring emissions on a territorial scale. The project also foresees the integration of advanced environmental monitoring solutions based on IoT technologies and Earth Observation satellite systems (Figure 2). Among the main instruments employed are the Smart Rainfall System (SRS) [25], which enables high-resolution urban-scale rainfall mapping through networks of opportunistic sensors using satellite microwave link (SML) technology, and AURA, a modular network of multi-parametric monitoring units for the continuous measurement of meteorological parameters and pollutant concentrations in both solid and gaseous phases of the atmosphere.

Figure 2. Environmental monitoring instrument (IoT air quality monitoring) installed inside the experimental case study site, the *Albergo dei Poveri* complex (Genoa).

As regards the data developed through remote monitoring, this strategy was developed by integrating multi-channel satellite data with advanced machine learning algorithms for predicting black carbon concentration. The methodology is based on two complementary methodologies. The first methodology uses gradient boosting algorithms (CatBoost) to solve a regression task aimed at estimating black carbon concentrations from structured tabular data from sensors installed in situ, as seen previously. These decision tree-based ensemble models can capture complex non-linear relationships between environmental variables such as particulate matter concentrations, temperature and relative humidity, effectively handling heterogeneous features and missing values. Once trained on data collected between 2013 and 2023, the model was applied to multi-channel satellite images from programs such as Copernicus Sentinel-2 and ERA5, where each channel represents a specific contextual parameter, allowing large-scale inferences with daily updates. The second methodology integrated Bayesian probabilistic models with Physics-Informed Neural Networks (PINN), combining experimental data from atmospheric chambers with satellite observations. The Bayesian model, calibrated using probabilistic programming techniques, provided posterior probability distributions that quantify the likelihood associated with Black Carbon estimates. This physical knowledge was incorporated as a constraint in the PINN loss function, allowing accurate predictions even with limited datasets.

The data collected by IoT sensors and satellites for all monitored pollutants are harmonized into a single information infrastructure, with the aim of correlating them with the observed degradation phenomena (Figure 2).

2.3. Methodology for the Recognition and Mapping of Degradation Phenomena and HBIM Representation

2.3.1. Architectural Survey Phase

The surveying phase was aimed at acquiring the geometry of the roof coverings of the complex through a series of surveying campaigns, while simultaneously identifying the most suitable methodology to ensure the accuracy and consistency of the acquired data. The goal of this phase was the production of high-resolution orthophotos, to be used as a basis for the subsequent architectural modeling and automated mapping of degradation phenomena. Specifically, the survey was aimed at acquiring the geometric configuration through aerial photogrammetric campaigns (SfM) using drones and, in specific cases, through Laser Scanning technology (tLS).

A preliminary phase of planning for the aerial survey with drone was carried out, integrating remote analyses (cartographic data, archival photographs) and on-site inspections to define the operational parameters, acquisition perimeters, obstacles, altitudes, and flight trajectories (Figure 3).

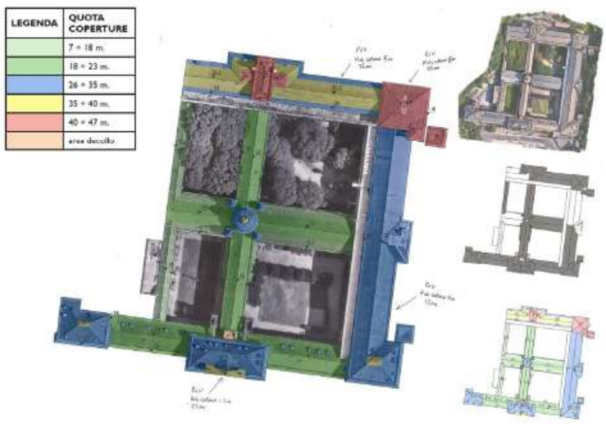


Figure 3. Preliminary Survey Plan for UAV Roof Coverage—*Albergo dei Poveri* complex (Genoa).

The mission was then designed within the cloud-based platform DJI FlightHub 2, specifically developed for the advanced management of UAV operations.

Subsequently, prior to the operational survey phase, the environmental parameters were recorded using a dedicated data sheet and integrated with the DJI Mavic 3T logs to verify operational stability (Figure 4).

Figure 4. Screenshot from DJI FlightHub 2 showing the flight-plan for one of the roof coverings of the *Albergo dei Poveri* complex (Genoa).

The operational activity involved automatic flight missions with shooting distances ranging between 8 and 5 m, to achieve a Ground Sample Distance (GSD) between 0.5 and 1 cm/pixel, a value considered suitable for the identification of micro-degradation phenomena such as cracks, flaking, and exfoliation. The test flights showed that a 5 m altitude ensures the best definition and data homogeneity, while a 6.3 m distance represents the optimal compromise for achieving uniform and manageable coverage across the entire roof surface (Figure 5).

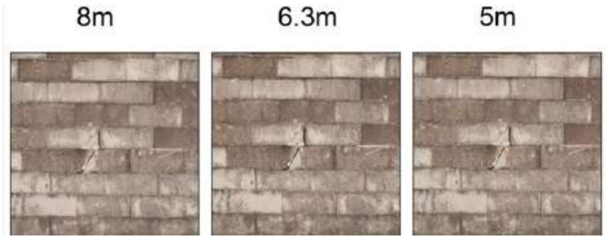


Figure 5. Visualization of the resolution of photographic surveys at different flight altitudes.

Photographic acquisitions were performed using both nadiral and oblique (45°) angles to improve three-dimensional reconstruction and surface readability, ensuring high image overlap (70–80%) and uniform diffuse lighting, while avoiding midday hours to minimize shadows and reflections. Where necessary, manual flight operations were carried out to capture details and critical areas. The RTK georeferencing of the model was carried out using a Trimble R10 GNSS station, ensuring centimeter-level accuracy.

In selected cases, a Laser Scanner technology (tLS) was employed to provide metric control, higher local point density, and verification of potential deformations or occlusions (Figure 6).

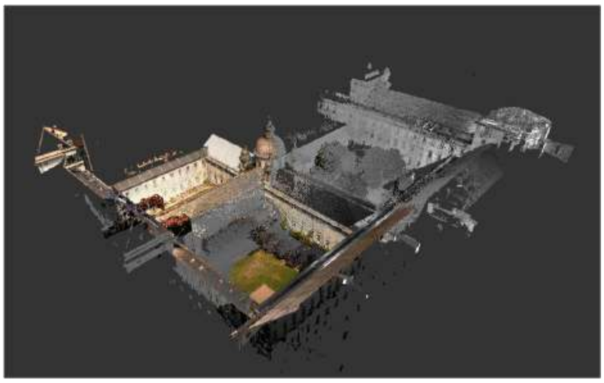


Figure 6. Visualization of the point cloud processed through tLS within Autodesk ReCap Pro 2025 software.

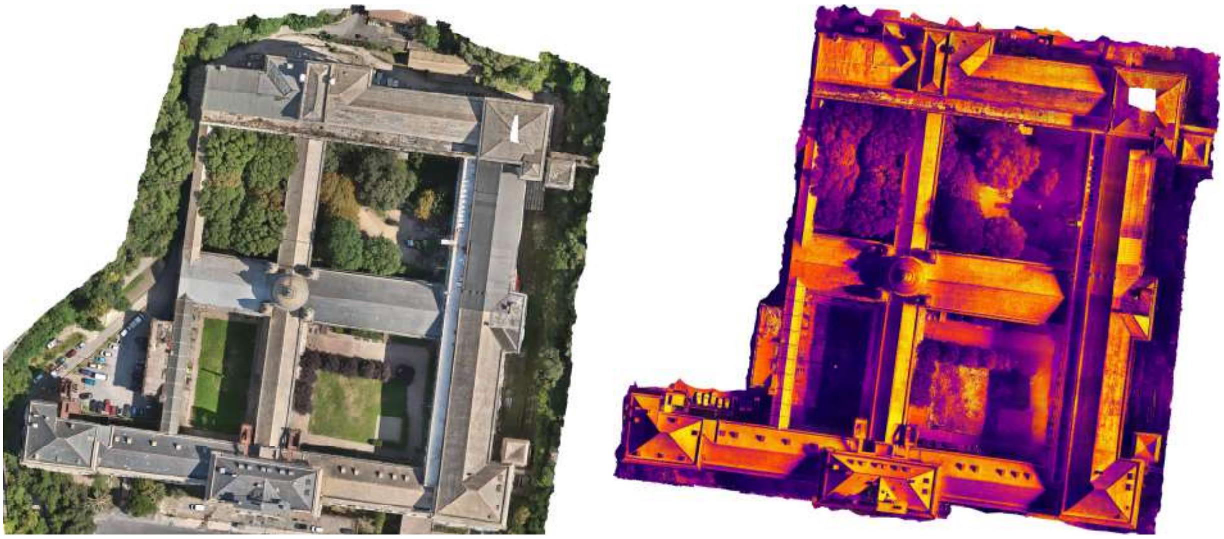
Following the operational survey phase, the point cloud was processed in Agisoft Metashape, performing Structure-from-Motion (SfM) alignment using reference markers and applying selective masking to manually exclude non-relevant portions of the images prior to point cloud generation.

Subsequent steps included dense cloud generation, mesh creation, and texturing, leading to the production of high-resolution RGB and infrared (IR) orthomosaics.

The thermograms were pre-processed in DJI Thermal Analysis Tool—standardizing scale, range, and contrast—and subsequently projected onto the same mesh to ensure spatial coherence between datasets.

For integrated visualization, the georeferenced orthomosaics were overlaid in AutoCAD 2022, converting the RGB layer to grayscale and adjusting the IR image transparency.

The final outputs intended for artificial intelligence training were exported in JPEG format, while those used for architectural modeling in HBIM environments were exported in Geo-TIFF format (Figure 7).



(a) (b)

Figure 7. *Albergo dei Poveri* complex: visualization of the RGB (**a**) and thermal (IR) (**b**) orthomosaics of the roofing system.

2.3.2. AI Technology—Training of the Algorithm for the Automatic Mapping of Degradation Phenomena

Starting from the orthophotos produced during the survey phase, artificial intelligence was applied to automatically classify the degradation phenomena on the roofs under study, using a machine learning process. The experiment was divided into two phases: a training phase, based on a series of pitched slate roofs for learning the algorithm, and a validation phase, in which artificial intelligence automatically recognized signs of deterioration.

The labeling process was carried out using CVAT (Computer Vision Annotation Tool), an open-source platform for creating annotated datasets from images. The high resolution of the orthophotos, essential for the identification of degradation phenomena, led to the exclusion of other platforms such as Label Studio and Labelbox, which were unable to handle high-resolution imagery.

The training process involved the manual annotation of degradation phenomena, testing two approaches: object detection and semantic segmentation. The former identifies and localizes distinct objects within an image but does not provide the level of detail required for in-depth analyses, whereas the latter assigns a label to each pixel, generating a detailed map that precisely distinguishes the different elements within the scene. The latter approach proved more effective for stone surfaces, as it enables a more accurate delineation of both architectural elements and degradation phenomena.

Specifically, a customized U-Net architecture was implemented for multi-class segmentation, adapted to handle inputs with 3 channels (RGB) or 4 channels (RGB + NIR) and a variable number of output classes. The implementation was developed using PyTorch and PyTorch Lightning (2.5.0 version), ensuring modularity and scalability. Given the high resolution of the images, a tile-based approach with random extraction during training was adopted to increase data variability and reduce the risk of overfitting.

Several data augmentation techniques were applied, including random flip, rotations in multiples of 90°, small zooms, and additional rotations to simulate distortions caused by variations in acquisition distance. During training, learning rate scheduling, early stopping, and checkpointing were implemented to optimize convergence and computational efficiency.

For the validation (or inference) phase, an aligned tiling strategy with overlaps was employed to reduce the effects of boundary artifacts. The predictions from individual tiles were subsequently merged to generate a complete segmentation map. The process was further enhanced through Test Time Augmentation (TTA), which aggregates multiple predictions to obtain final estimates that are as robust and reliable as possible.

2.3.3. HBIM Model

In this phase, the objective was the development of a digital model serving as the architectural-operational foundation for automatic mapping and information management activities, without delving into the geometric accuracy of individual components of the building envelope. The main goal was to define an essential geometric and informational content, comparable to that of a feasibility study, in which the principal elements of the envelope were modeled.

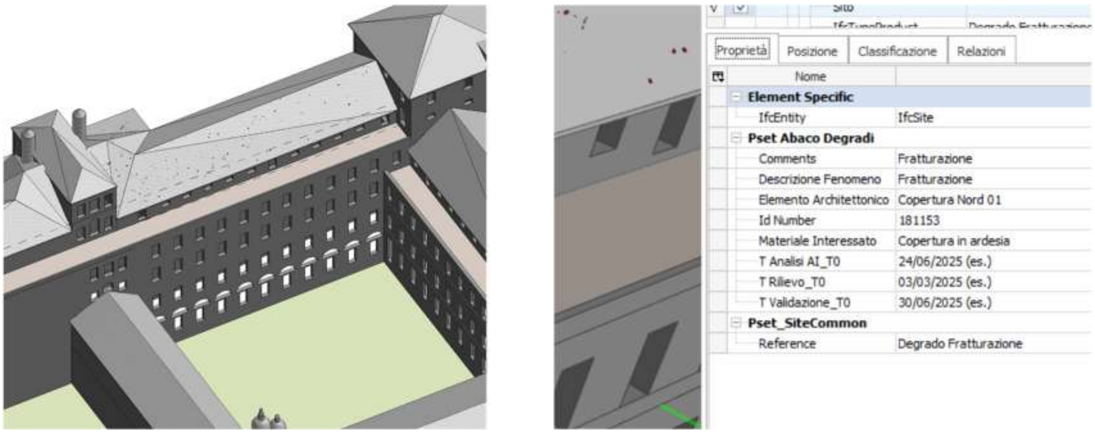
The model, conceived as an information container for degradation conditions, employed architectural elements as hosts for the insertion of degradation instances, represented as parametric families.

Specifically, the model was structured according to a Level of Development (LOD) B, as defined by UNI 11337-4, characterized by a low geometric detail, to prioritize informational use and reduce time-consuming modeling activities.

Simplified representations of walls, floors, roofs, terraces, and openings were included.

The insertion of geometric and informational data was automated through scripts applied to the results of the AI training phase, followed by technical validation.

Each degradation instance was described through a Property Set containing numeric ID, phenomenon description, damage level, associated architectural element, affected material, and geometric dimensions such as area or linear extent. The temporal dimension of the data was managed through the parameters T_Survey_T0/T1 and T_Validation_T0/T1 (Figure 8).



(**a**) (**b**)

Figure 8. *Albergo dei Poveri* complex (Genoa): (**a**) visualization of the HBIM model within the Autodesk Revit environment; (**b**) detail of the parameters entered for the modeled roofing system.

The system was georeferenced in WGS84 and federated across three integration levels, enabling data querying, traceability, and versioning.

Interoperability was ensured through export in open-BIM (IFC) format and subsequent publication on an open-source platform specifically developed for the informative management of the asset, as described in the following sections. The workflow adopted for the modeling of degradation phenomena and the subsequent export phase of the digital model is illustrated in Figure 9.

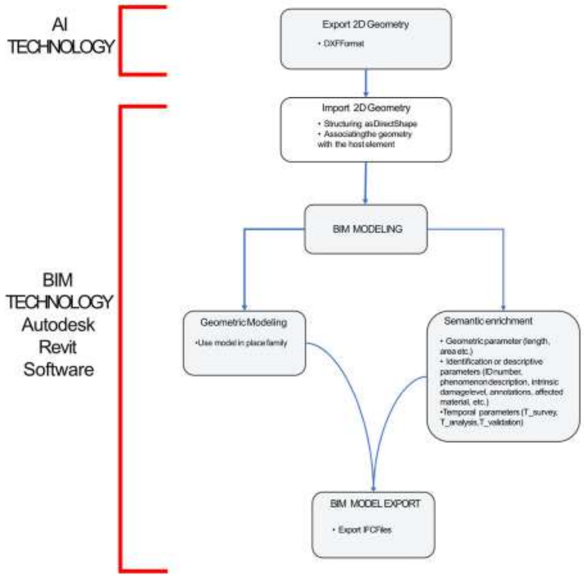


Figure 9. Workflow for the modeling of degradation phenomena and the export phase of the digital model.

2.4. A Management Platform for Diagnostics in Historic Building Conservation Through Digital Twin Technology

The EN-HERITAGE platform serves as a digital environment capable of integrating the collection, management, and analysis of data derived from all previously described phases. The system was developed to provide heritage managers with an initial operational tool for diagnosis, planning, and conservation management, following the Digital Twin paradigm.

The platform architecture is structured across three functional layers—data, processing, and presentation. The first layer manages the acquisition and organization of multisource data, collected from 3D surveys, IoT sensors, and satellite observations, supporting visualization and analysis at the urban scale. The second layer is dedicated to the processing, validation, and correlation of datasets, leveraging artificial intelligence algorithms for the automatic detection and classification of degradation phenomena at the building scale. The third layer, oriented toward presentation, provides visualization and interaction tools through a three-dimensional WebGIS interface implemented using the Cesium Ion platform [26], complemented by an integrated web-based BIM viewer for consulting the developed HBIM model (Figure 10).

Whenever new roof surveys and updated orthophotos are produced, the platform architecture is designed to automatically generate a new segmentation and classification of degradation phenomena. The resulting instances are integrated into the HBIM model and exported to the web platform as a new temporal state representing the condition of the roofing systems. Through the Cesium-based interface, users can inspect the automatically generated maps, validate or correct the assigned classes, and edit the associated properties (e.g., damage level, extent, material, and temporal references). This workflow combines an automated assessment of conservation conditions with an expert-driven refinement process, ensuring that the digital representation dynamically evolves as new observations and surveys become available.

The system enables multilevel visualization, from the urban to the architectural scale, integrating real-time analysis, querying, and updating functionalities to support monitoring and preventive maintenance. The management of environmental, thermal, and geometric datasets is handled by a centralized data lake, ensuring data consistency, traceability, and integrity. Fully interoperable with openBIM (IFC) and GIS standards, the platform provides a shared information environment that integrates geometric surveys, diagnostic data, environmental measurements, and historical documentation. Thus, EN-HERITAGE establishes itself as a collaborative environment where heritage authorities, professionals, and public administrations can share information and coordinate conservation strategies effectively.

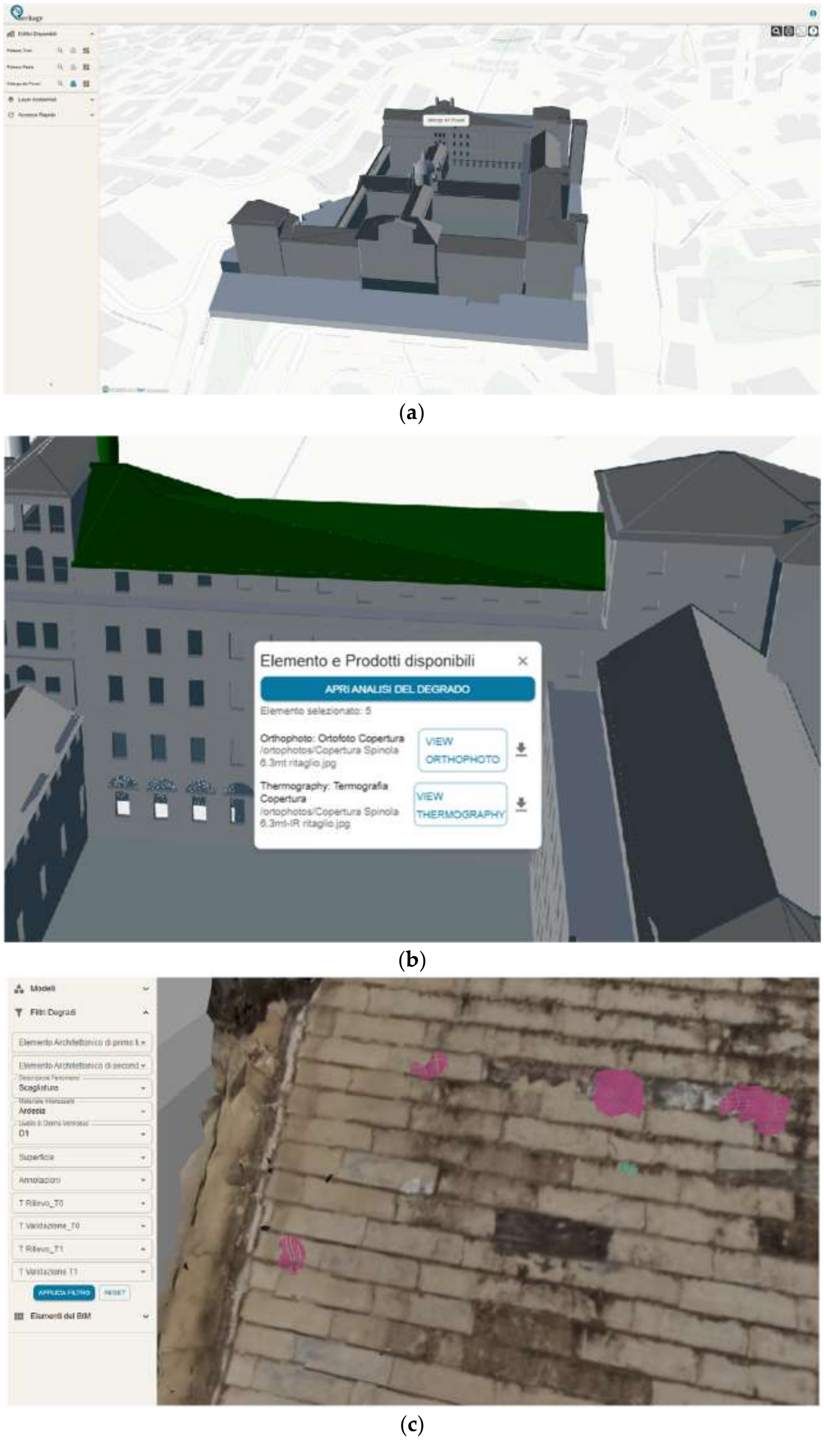


Figure 10. EN HERITAGE platform: (**a**) building selection interface; (**b**) component-level inspection; (**c**) attribute-based filtering of degradation phenomena.

3. Results

3.1. Results of the Environmental Monitoring Phase

Environmental monitoring activities provided a structured dataset useful for the characterization of the atmospheric context and the distribution of pollutants within the reference area. The experimental phase enabled the collection and integration of a significant amount of environmental data from in situ sensors, opportunistic IoT networks, and satellite observations, consistent with the integrated model proposed by EN-HERITAGE for environmental data acquisition and management; however, the spatial and temporal resolution of these data, generally referring to broader scales than those of the analyzed degradation phenomena, did not always support a point-specific and direct correlation with the processes observed at the local level.

3.2. Results of Degradation-Phenomena Mapping and HBIM Representation Methodology

3.2.1. Results of the Architectural Survey Phase

The survey campaign produced an integrated set of metric, photogrammetric, and thermographic results aimed at documenting and analyzing the roofs of the complex. The processing of data acquired through aerial drone survey (SfM) and terrestrial laser scanning technology (tLS) enabled the generation of high-resolution RGB and IR orthophotos (GSD 0.5–1 cm/pixel), georeferenced point clouds, and textured 3D models, ensuring accurate and morphologically consistent restitution.

The integration of these different datasets allowed the production of analytical outputs for the automated mapping of degradation and the assessment of the conservation condition of materials.

The final products, exported in interoperable formats (JPEG and GeoTIFF), provided a solid foundation for subsequent phases of architectural modeling in the HBIM environment and for the training of artificial intelligence algorithms dedicated to the recognition of degradation phenomena.

The entire process also enabled the definition of a replicable operational protocol, ensuring traceability, accuracy, and consistency between survey, processing, and representation, within a framework of integrated and digital management of the built heritage.

3.2.2. Results of AI Technology—Training of the Algorithm for the Automatic Mapping of Degradation Phenomena

The validation phase of the deep learning algorithm demonstrated the effectiveness of the custom UNet-based approach for multiclass semantic segmentation of degradation phenomena on the roof surfaces of historic buildings. The model, developed using the PyTorch and PyTorch Lightning frameworks, was trained on a manually annotated dataset created in CVAT, consisting of high-resolution RGB orthophotos acquired during photogrammetric survey campaigns.

The implemented neural architecture showed remarkable operational flexibility, allowing dynamic configuration of critical parameters such as the number of input channels (supporting both 3-channel RGB and 4-channel near-infrared configurations), the variable number of output classes, and the ability to operate in both multiclass and multilabel modes, since some categories are mutually exclusive while others may coexist. The optimized handling of high-resolution imagery through a tile-based approach enabled efficient processing of large-scale orthomosaics while maintaining high precision in the morphological delineation of degraded areas.

The implementation of Test Time Augmentation (TTA) within the inference pipeline further enhanced predictive robustness. The aggregation of multiple predictions obtained through controlled transformations and overlapping tiling minimized edge artifacts, ensuring continuity and consistency in the final segmentation map. Optimization strategies such as learning rate scheduling, early stopping, and periodic checkpointing ensured efficient model convergence while maintaining a balance between accuracy and computational sustainability.

Since the classification model was designed to operate in a mutually exclusive multi-class mode, it was not possible to assign multiple degradation categories to the same pixel simultaneously. Consequently, during the training phase, only non-coexisting phenomena—such as cracks, fissures, and exfoliation—were mapped, while during the validation phase, pixel-wise semantic segmentation enabled the accurate identification of critical phenomena such as exfoliation and fractures of slate tiles. The data augmentation techniques implemented during training, including geometric transformations, significantly improved the model's generalization ability and reduced the risk of overfitting.

The results for the model validation (both with and without TTA) are presented below (Tables 2 and 3).

Table 2. Model results in standard inference (No TTA).

NO TTA—No Test Time Augmentation	
Accuracy	0.9482
F1	0.4890
Normalized Confusion Matrix	0.9483–0.4312 0.0517–0.5688

Table 3. Model results in inference with Test-Time Augmentation (TTA).

TTA—Test Time Augmentation	
Accuracy	0.9637
F1	0.4944
Normalized Confusion Matrix	0.9638–0.3804 0.0362–0.6196

These results were obtained with the following training set:

- Number of images: 7;
- Average number of pixels for image: 100 million (e.g., 10.000 × 10.000);
- Tile size: 256 pixel;
- Number of tiles in the set: 10.936 randomly re-generated at each epoch;
- Positive pixel incidence: 5/10.000.

And validation set:

- Number of images: 2;
- Average number of pixels for image: 125 million;
- Tile size: 256 pixel;
- Number of tiles in the set: 3.874 randomly generated (fixed for all the training process);
- Positive pixel incidence: 5/10.000.

3.2.3. Results HBIM Model

The methodology produced a coherent degradation database, where each instance is identifiable and traceable over time (T0/T1), with a clear separation between survey data, automated detection output, and expert validation.

The normalization of Property Sets enables thematic queries by phenomenon, material, damage level, and building element. The adoption of a Level of Detail (LOD) B accelerated updates, reduced geometric conflicts, and ensured the sustainability of the process in terms of maintenance.

The use of DirectShape minimized manual modeling on large volumes, while federation with the textured mesh improved readability and control within the real-world context.

The export in IFC/OBJ formats and subsequent publication on the Cesium platform enabled web-based visualization, interdisciplinary data sharing, and temporal comparison.

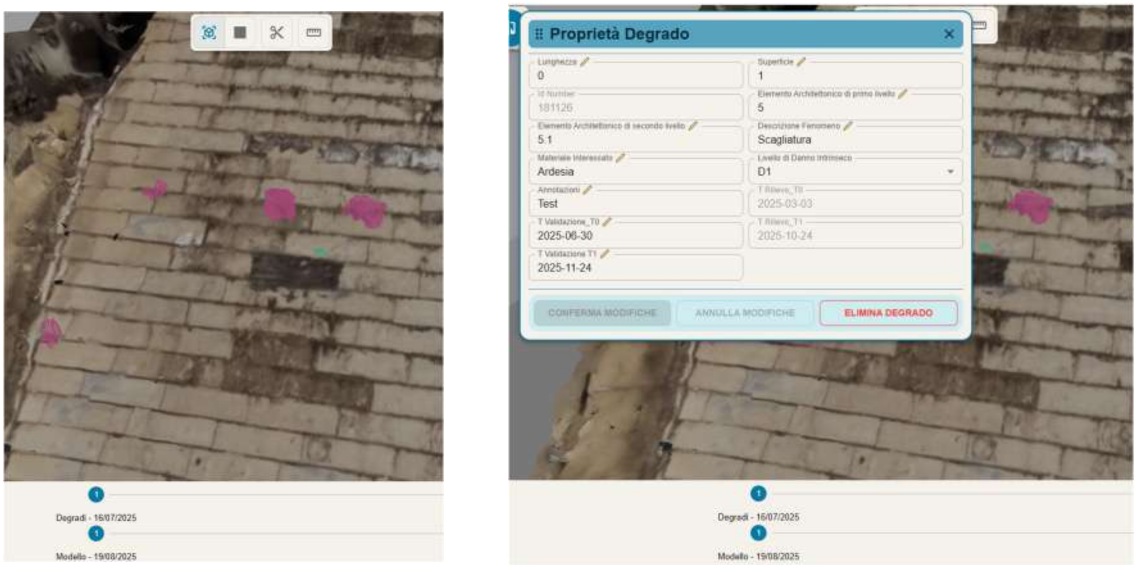
As a result, the workflow supports more robust prioritization of interventions, greater process transparency, and the reusability of the methodology for future survey campaigns.

3.3. Results of Platform for Diagnostic in the Conservation and Use of Historic Buildings Through Digital Twin Technology

The development of the EN-HERITAGE platform represented one of the main outcomes of the project, leading to the implementation of an integrated system for the management of environmental architectural information related to the case study.

The platform enabled the correlation of data acquired from monitoring and surveying systems with the geometric and semantic models of the building, providing users with an interactive and dynamic environment for data consultation and analysis.

Specifically, users were able to access environmental measurements, visualize architectural surveys, and interact with the mapped degradation phenomena on building surfaces, performing comparisons between two different timeframes and modifying the properties of each individual degradation instance represented within the model (Figure 11).



(**a**) (**b**)

Figure 11. (**a**) Visualization of degradation areas on the surface of a case-study roof within the Cesium platform; (**b**) pop-up panel displaying the related properties, which can be viewed and edited by the user for a selected area (highlighted in green).

The implementation of these functionalities constitutes a prototype of a dynamic platform, supported by the automated real-time ingestion of environmental data streams and the synchronized updating of building exposure dashboards. Environmental parameters collected by Air Quality (AQ) monitoring nodes are updated at 5 min intervals, while rainfall measurements acquired through the Smart Rainfall System (SRS) are refreshed at 1 min intervals, ensuring a continuously updated representation of the building's environmental context.

4. Discussion

4.1. Discussion Results of the Enviromental Monitoring Phase

From a methodological perspective, the experimental results indicate that the integration of IoT technologies and in situ observation data represents a viable strategy for supporting a dynamic and up-to-date characterization of environmental conditions relevant to material degradation processes. The use of smart IoT sensors enabled the acquisition of high temporal resolution data, providing a detailed view of variations in pollutant concentrations in proximity to the monitored buildings.

At the same time, the integration of satellite data with direct measurements expanded the observation scale, allowing the identification of territorial areas characterized by higher exposure levels and supporting the definition of geographically based preventive strategies.

During the monitoring campaigns focused on Black Carbon (BC), the measurements produced detailed temporal profiles, revealing distinct daily cycles. The results show that concentrations were strongly influenced by vehicular traffic and residential heating, the main sources of carbonaceous aerosols in urban environments. The peak values recorded were consistent with those typically observed in the city of Genoa, indicating that the monitored area is exposed to pollutant levels comparable to those of the surrounding urban context (Figure 12) (Table 4).

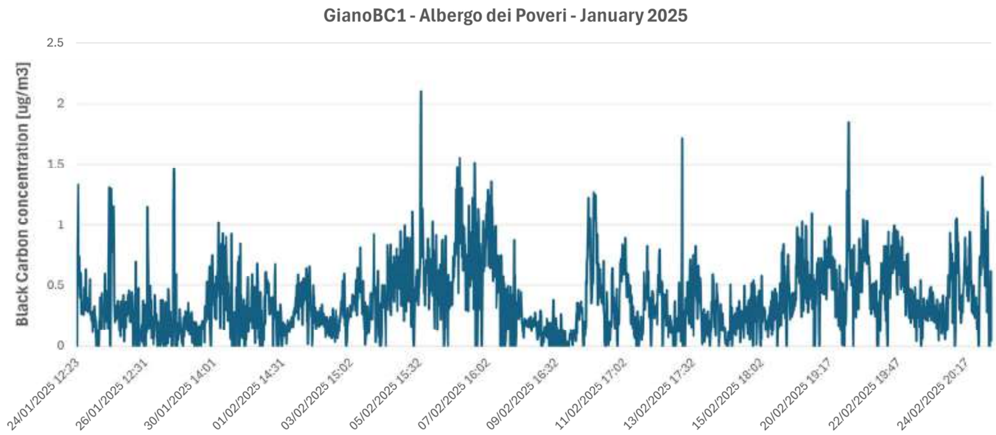


Figure 12. Results of the monitoring activities of Black Carbon (BC) concentration in the *Albergo dei Poveri* complex (Genoa).

Table 4. Summary of Black Carbon monitoring campaign results.

Site Name	Maximum Observed Value (ug/m^3)	Average Observed Value (ug/m^3)
Albergo dei Poveri complex	2.10	0.40

Since no reliable low-cost technology is available for the monitoring of Black Carbon and it has not been standardized as a continuous process, data acquisition could be performed only during limited, temporary measurement campaigns, which limits the continuity of observation. In addition, the data obtained through satellite-based inference still have insufficient resolution for detailed assessments at local or zonal scales. Within these constraints, the monitoring activities confirmed the replicability of the operational model in different urban contexts, supported by its relatively low costs, scalability, and high level of automation in data acquisition and management processes. At the same time, the data collection and harmonization infrastructure developed within the EN-HERITAGE project proved effective in spatially densifying environmental information and in constructing a coherent, multi-scale framework of the main atmospheric variables.

Overall, these results provide a consistent basis for the future development of predictive models aimed at exploring correlations between environmental parameters and degradation phenomena, in line with the evolutionary objectives of the system.

The interpretation of environmental data becomes particularly relevant when analyzed in relation to material degradation processes, although it is not always straightforward due to the different spatial and temporal scales characterizing the available datasets. Within the research activity, specific descriptive sheets were developed to characterize the mechanisms and processes associated with the different types of degradation potentially affecting slate roofing systems. This information was systematically organized to explore possible correspondences between the environmental data recorded by the in situ IoT monitoring network and the degradation processes observed on the building surfaces (Figure 13).

	Anthropogenic pollutant emissions				Air humidity	Ventilation		Temperature			Solar explosure	
	Nitrogen oxides (NOX)	Sulfur oxides (SOX)	Carbon dioxide (CO_2)	Atmospheric particulate matter (pm 2.5 - pm10)	Relative humidity > 60%	Low	High	> a 20°C	< a 5°C	Escursione termica	High	Low
Biological collonization					x	x		x			x	
Biological patina					x	x						
Surface deposit				x								
Detachment					x				x			
Surface erosion	x	x	x		x		x					
Exfoliation	x	x	x		x				x			
Fissuring					x				x	x		
Fracturing					x				x	x		
Flaking					x				x	x	x	
Loss of material					x				x			

Figure 13. Visualization of environmental factors potentially involved in the initiation and progression of degradation phenomena.

Several forms of degradation, such as fracturing and flaking, appear to be primarily influenced by thermal and hygrometric dynamics. These phenomena are generally associated with physical actions developing at material discontinuities or weak zones, where micro-infiltration, moisture migration, and freeze–thaw cycles contribute to the initiation and evolution of degradation processes. In this context, precipitation data acquired through the Smart Rainfall System (1 min temporal resolution) and relative humidity (Figure 14) and temperature profiles (Figure 15) measured by the AQ nodes (5 min temporal resolution) provide indications of environmental conditions potentially favorable to such mechanisms.

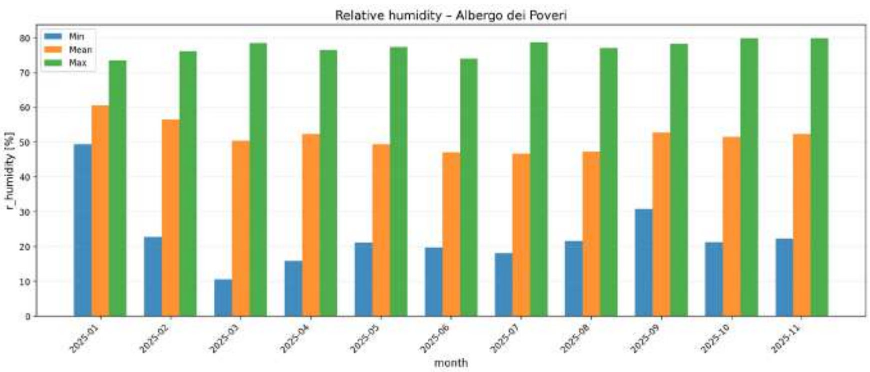


Figure 14. Results of the monitoring activities of relative humidity in the *Albergo dei Poveri* complex (Genoa).

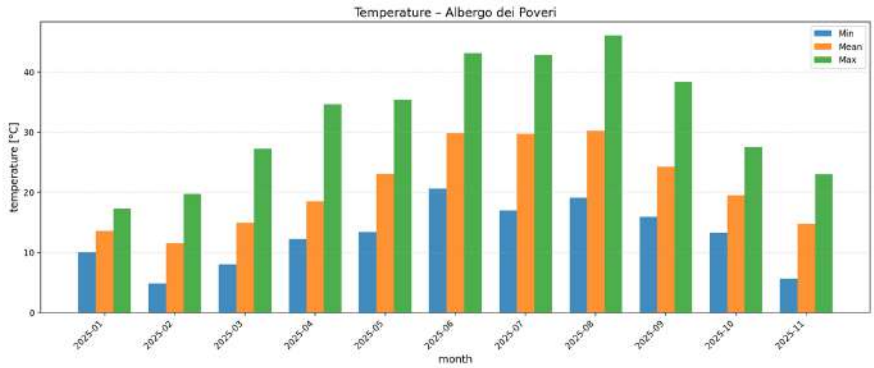


Figure 15. Results of the monitoring activities of temperature in the *Albergo dei Poveri* complex (Genoa).

Other degradation typologies, including the formation of surface deposits and, in part, slate exfoliation, are mainly associated with atmospheric pollution and particulate deposition, in combination with additional environmental factors (Figure 16). In this sense, the Black Carbon cycles observed during the monitoring campaign represent a significant indicator of pollutant exposure, particularly in roof areas characterized by limited wash-off or reduced runoff.

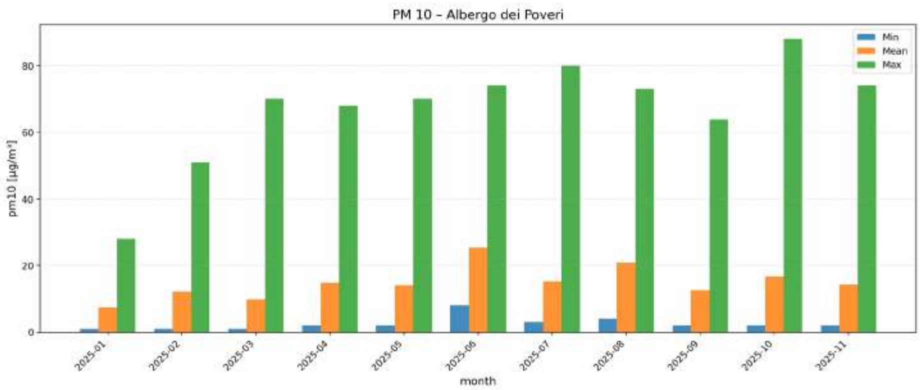


Figure 16. Results of the monitoring activities of PM 10 in the *Albergo dei Poveri* complex (Genoa).

Similarly, biological colonization and patina formation are favored by conditions of high humidity, limited ventilation, and persistent shading, frequently observed in north-oriented roof sections. The environmental monitoring system enables the mapping of these microclimatic conditions and their comparison with the spatial distribution of biological growth identified through the artificial intelligence-based analysis model.

Overall, the integration of high-frequency environmental data with the spatial mapping of degradation phenomena enables, through the EN-HERITAGE platform, a more articulated interpretation of degradation processes. This approach provides a knowledge-based support for the future development of predictive models aimed at analyzing relationships between environmental factors and material response, while explicitly accounting for differences in scale among the available datasets.

4.2. Discussion Results of the Automatic Degradation Mapping Methodology

The methodology developed for the recognition and mapping of degradation phenomena demonstrated the effectiveness of combining advanced surveying techniques with artificial intelligence algorithms, establishing itself as an innovative approach to the planned conservation of historic buildings.

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The implementation of a semantic segmentation algorithm based on a customized UNet architecture, trained through manual annotations performed using CVAT, enabled pixel-wise automatic classification of specific degradation phenomena.

The use of PyTorch Lightning facilitated model scalability, while the tile-based approach allowed efficient management of high-resolution imagery and provided a natural mechanism for data augmentation through random tiling.

The main challenges addressed concerned the balancing of degradation classes, which were unevenly distributed within the datasets, and the handling of environmental variability in acquisition conditions.

However, some limitations remain: the need for manual annotations in the initial training phase slows down implementation on new case studies; the dependence on orthophoto quality requires controlled operating conditions; and the validation of the algorithm for coexisting or underrepresented degradation types demands additional datasets.

Future developments include expanding the range of detectable classes and integrating multispectral sensors to enhance the system's diagnostic capability.

The experimental results confirm the scalability of the proposed approach and its applicability to different types of surfaces and degradation patterns. The architectural modularity allows future integration with thermographic data and environmental sensor information, opening perspectives for the development of integrated automated monitoring systems. The spatial correlation between thermal anomalies and visible degradation, obtained through orthomosaic overlay, represents a promising element for the development of advanced diagnostic strategies based on multimodal analysis of historic building surfaces.

4.3. Discussion Results of Platform for Diagnostic in the Conservation and Use of Historic Buildings Through Digital Twin Technology

The EN-HERITAGE platform represents a significant advancement in the digitalization of historic heritage, enabling the integrated management of architectural and environmental information. Information management based on the BIM methodology is consistent with widely adopted international standards. openBIM export, based on IFC standards certified by buildingSMART, provides a robust foundation for defining structured information content, both in terms of data coding and interoperability, as well as data extraction.

The balance between the established capability to produce geometric content and the need to link it to structured information constitutes the main methodological focus of the development. The objective is to promote the use of open data structures and to reduce information fragmentation, thereby improving the overall efficiency of data management.

The adoption of cloud architectures and Web-GIS interfaces facilitates data sharing and collaboration among different stakeholders. Interactive analysis functions and three-dimensional visualization, oriented toward a Digital Twin-based approach, enable complex technical data to be transformed into operational tools supporting the planning of restoration and maintenance interventions.

Future developments include the integration of a document management section, enabling digital building entities to be linked to technical reports, datasheets, drawings, records of past interventions, and cadastral information. This approach strengthens the platform's role as a collaborative environment, promoting information sharing among heritage authorities, professionals, and public administrations. The system is also designed to integrate alerting functions and decision-support tools for conservation planning.

In addition to the technical validation of the platform, the project included a preliminary phase of stakeholder engagement involving institutional bodies responsible for the conservation of Genoa's historic built heritage. Several stakeholders formally expressed their support through letters of interest submitted during the funding application phase (POR FESR), confirming both the operational relevance of the proposed tool and their willingness to participate in future testing and evaluation activities. The platform's functionalities are also consistent with the strategies outlined in the Genoa 2050 Action Plan, particularly about the digitalization of heritage management processes and the integration of environmental monitoring into conservation planning.

In a subsequent phase, with the *Albergo dei Poveri* case study representing the most complete implementation of the EN-HERITAGE workflow, heritage authorities and technical professionals will be involved in structured testing sessions aimed at assessing usability, diagnostic effectiveness, and the platform's contribution to the prioritization of conservation interventions. This phase will provide a qualitative and operational validation of the platform's decision-support capabilities.

In conclusion, the implementation confirmed the replicability of the model in other contexts, thanks to the use of open-source technologies and the adoption of interoperability standards (OGC, IFC). In its prototype version, the EN-HERITAGE platform acts as an operational Decision Support System (DSS) [27], capable of integrating multi-source data and providing a comprehensive and up-to-date overview of the conservation state of historic buildings, supporting strategic planning and effective management of architectural heritage. The system currently operates as a support platform; however, its architecture has been designed to enable future extensions, particularly through the progressive inclusion of architectural survey products aimed at analyzing the temporal evolution of degradation phenomena, supporting predictive modeling, what-if simulations, and long-term evolution analyses.

5. Conclusions

The EN-HERITAGE project demonstrated the technical and operational feasibility of an integrated approach to the management of historic architectural heritage, based on the synergy between environmental monitoring technologies, architectural surveying, digital modeling, and predictive analysis.

The proposed approach combines the use of innovative sensors, satellite observation technologies, and digital decision-support platforms to enhance the knowledge and conservation of historic buildings.

The activities carried out highlighted how the integration of satellite data, IoT sensors, and HBIM models enables the construction of a dynamic and multidimensional understanding of the conservation state of buildings, supporting a multidisciplinary interpretation of heterogeneous datasets and fostering more efficient and sustainable management practices. This integration supports a multidisciplinary interpretation of heterogeneous datasets, in which environmental information and architectural data jointly contribute to the analysis of degradation processes and conservation needs, fostering more efficient and sustainable management practices.

The project has revealed a structural challenge: environmental and architectural datasets display intrinsic spatial and temporal scale mismatches that translate into broader issues of model interoperability. Their integration requires rigorous multiscale harmonization and clearly defined methodological protocols. These findings underscore the need to further develop, validate, and standardize data-fusion and model-interoperability frameworks capable of managing scale, semantic, and structural discrepancies in a controlled manner.

Beyond the technical results, the project contributed to consolidating a new strategic vision for cultural heritage conservation, in which digitalization, data analysis, and predictive modeling become key tools to improve knowledge, reduce maintenance costs, and increase the resilience of historic assets to climatic and environmental changes.

Looking ahead, the EN-HERITAGE platform represents a transferable operational model. However, the scalability of the system is primarily methodological: the model can be transferred to other roofing systems, whereas its extension to other building elements is more complex and strongly dependent on data availability and interoperability. Its modularity, interoperability, and scientific foundation constitute a solid starting point for further developments aimed at the creation of intelligent, automated systems for diagnostics, monitoring, and decision support, benefiting public administrations, heritage authorities, and professionals in the field.

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