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1.1 Document History

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2 Abstract

The increasing frequency and intensity of natural hazards under a changing climate demand innovative and scalable approaches for vulnerability and exposure assessment. Within the RETURN project, Deliverable DV3.6.1 presents a comprehensive framework for data exploitation aimed at enhancing vulnerability modeling through advanced machine learning (ML) and artificial intelligence (AI) techniques. The report addresses the methodological and technological challenges associated with integrating heterogeneous, multi-modal datasets—including satellite imagery, UAV surveys, IoT sensor streams, and crowdsourced geospatial information—into interoperable and scalable modeling pipelines.

The proposed framework is structured around three interdependent pillars: (i) data harmonization and structuring, ensuring spatial, temporal, and semantic consistency across diverse data sources; (ii) feature engineering, transforming raw observations into meaningful structural, environmental, and socio-economic indicators; and (iii) ML/AI pipeline development, enabling predictive vulnerability scoring and debris estimation through state-of-the-art algorithms such as Convolutional Neural Networks (CNNs), Gradient Boosting Machines (GBM), and Graph Neural Networks (GNNs). Attention is devoted to explainable AI (XAI) techniques to enhance transparency and trust in model outputs, as well as to synthetic data generation and transfer learning strategies to mitigate data scarcity.

The deliverable also presents a structured acquisition workflow, addressing interoperability challenges and computational scalability through cloud-based infrastructures and standardized geospatial protocols. Validation and benchmarking procedures are discussed to ensure model robustness and reproducibility, including the use of real and synthetic datasets and cross-domain evaluation metrics.

In parallel, the report develops and applies exposure and vulnerability models for multi-hazard analyses, including seismic events, volcanic ashfall, and pyroclastic flows. Building-level vulnerability classification is performed using the S.A.V.E. methodology, while large-scale assessments leverage statistical inference models (B.I.N.C.) integrated with national aggregated datasets. The framework is demonstrated through a case study in the Phlegrean Area, highlighting the operational applicability of the proposed methodologies for territorial-scale resilience assessment.

Overall, DV3.6.1 establishes a scalable, interoperable, and innovation-driven ecosystem for vulnerability modeling. By combining remote sensing technologies, AI-driven analytics, and multi-hazard exposure databases, the proposed approach supports proactive disaster risk reduction and evidence-based resilience planning at regional and national scales.

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4 AI health monitoring algorhitms

Disaster risk reduction and resilience planning are central to sustainable development, particularly as the frequency and intensity of hazards such as earthquakes, floods, hurricanes, and wildfires increase. Effective mitigation depends on accurate, dynamic models of vulnerability and exposure, grounded in high-quality, multi-dimensional data capturing both infrastructure fragility and socio-economic conditions. Traditional approaches—based on static inventories and empirical fragility curves—present significant limitations: they do not reflect real-time changes in building stock or population distribution and struggle to incorporate uncertainty or evolving hazard profiles, as highlighted by Rossetto et al. (2014) and Lagomarsino & Giovinazzi (2006).

Advances in remote sensing, IoT, machine learning (ML), and artificial intelligence (AI) offer transformative solutions. High-resolution satellite imagery, UAV surveys, and continuous sensor monitoring enable rapid and large-scale data acquisition, while ML/AI techniques process heterogeneous datasets and provide predictive insights for decision-making. Studies by Dell'Acqua & Gamba (2012) and Li et al. (2021) demonstrate the effectiveness of integrating remote sensing with AI for automated damage detection, and Cimellaro et al. (2019) together with Cardoni & Cimellaro (2025) highlight the role of ML in predicting post-earthquake debris distribution.

TK3.6.1 responds to these challenges by focusing on the acquisition and harmonization of diverse data sources and the application of AI-driven methods for vulnerability and exposure modeling. The objective is to develop a scalable, adaptive framework that supports real-time decision-making and enhances resilience, in line with the Sendai Framework for Disaster Risk Reduction (UNDRR, 2015).

The main objectives of this deliverable are: to define a data exploitation framework that supports vulnerability and exposure modeling using advanced computational techniques; to implement ML/AI-based workflows for predictive modeling of structural damage and debris distribution; to validate the proposed methodologies through benchmarking and case studies, leveraging recent research such as [J117], [BC15], and [C219].

The report covers: a review of state-of-the-art techniques in data acquisition and exploitation for disaster risk assessment; methodologies for multi-modal data integration and preprocessing; ML/AI approaches for predictive vulnerability modeling, including deep learning and explainable AI; Recommendations for future research and operational deployment within the CRISES platform.

By combining remote sensing technologies with data-driven modeling, this deliverable aims to establish a robust foundation for next-generation vulnerability assessment tools, enabling proactive disaster management strategies across Europe.

4.1 State of the art

The assessment of vulnerability and exposure in disaster risk management has evolved from empirical fragility curves and heuristic models to **data-driven approaches leveraging ML/AI and remote sensing**. This paradigm shift enables dynamic, scalable, and automated workflows for hazard prediction, damage detection, and resilience planning.

Recent literature emphasizes:

- **Remote sensing integration** for large-scale exposure mapping (Janga et al., 2023; Strong et al., 2025).

- **Deep learning for structural damage and debris prediction**, including convolutional neural networks (CNNs), transfer learning, and multimodal fusion ([J117]; [C219]; Jia & Ye, 2023).
- **AI foundation models** for geospatial tasks, enabling fine-tuning for vulnerability modeling (Lu et al., 2024).
- **Explainable AI (XAI)** for interpretability in risk assessment (Linardos et al., 2022).

4.1.1 Remote sensing and exposure modeling

Remote sensing technologies (Sentinel-1 SAR, Sentinel-2 MSI, LiDAR) combined with AI have enabled **global exposure mapping** and physical vulnerability characterization (Dimasaka et al., 2024). Deep learning models such as **ResNet-50** have been successfully applied to classify informal settlements and building typologies, addressing data scarcity in least developed countries. Challenges include:

- **Data heterogeneity** across sensors.
- **Interoperability** for multi-source integration.
- **Domain adaptation** for transferring models across regions ([Strong et al., 2025]).

4.1.2 Machine learning for Vulnerability and Debris Prediction

The application of machine learning (ML) in vulnerability modeling and debris prediction marks a major advancement in disaster risk assessment. Traditional empirical models based on deterministic fragility curves and heuristic assumptions are often unable to capture the complexity and variability of post-disaster environments. In contrast, ML provides data-driven and adaptive frameworks capable of learning from heterogeneous datasets and producing accurate predictions under uncertainty.

Recent studies, including Cardoni & Cimellaro (2024) [J117] and Elahi et al. (2025) [C219], demonstrate the strong predictive performance of ML for post-earthquake debris estimation, a key factor for emergency logistics and accessibility planning. Algorithms such as gradient boosting and ensemble methods effectively handle feature-rich datasets combining structural, hazard, and socio-economic variables, with gradient boosting traditional regression models in capturing non-linear relationships.

ML has also transformed image-based damage detection through Convolutional Neural Networks (CNNs), which analyze high-resolution UAV and satellite imagery for rapid, automated assessments. Li et al. (2021) and Fan et al. (2025) report global earthquake-induced landslide prediction accuracy exceeding 80%, confirming the scalability of deep learning approaches. To address class imbalance in disaster datasets, techniques such as SMOTE (Panda et al., 2025) improve model generalization by oversampling minority damage classes. Performance metrics further highlight ML superiority, with AdaBoost achieving an AUC of 0.93 for building damage classification (Patten et al., 2024). Overall, ML enables a shift from static pre-event estimations to dynamic, real-time analytics, supporting more effective disaster response and resource allocation.

4.1.3 Multimodal and explainable AI approaches

Emerging research advocates **multimodal fusion** of geospatial, structural, and socio-economic data for vulnerability modeling. Techniques include:

- **Contrastive learning** for vulnerability representation (Li et al., 2025).
- **Graph-based models** integrating building topology and hazard intensity (Ren et al., 2025).

- **Explainable AI** to interpret feature importance and model decisions, critical for policy adoption ([Linardos et al., 2022]).

Despite progress, key gaps remain:

- **Data scarcity** for rare hazards and low-income regions.
- **Model generalization** across diverse geographies.
- **Integration of real-time IoT and social media data** for dynamic vulnerability assessment.
- **Ethical and privacy concerns** in large-scale data exploitation (Albahri et al., 2024).

4.2 Data acquisition methodologies

Data acquisition for vulnerability and exposure analysis requires integrating heterogeneous sources, ensuring interoperability, and applying preprocessing techniques to enable ML/AI exploitation. The methodologies combine **remote sensing**, **IoT-based monitoring**, and **crowdsourced data**.

4.2.1 Data sources

The effectiveness of vulnerability and exposure analysis depends on the quality and diversity of data sources. Modern disaster risk assessment increasingly relies on multi-modal data capturing both physical and social dimensions of risk. Four key categories are particularly relevant: satellite imagery, UAV/drone mapping, IoT sensor networks, and open data with crowdsourced information.

Satellite imagery provides large-scale, consistent monitoring of structural and environmental conditions. Optical images support detailed inspection of urban features, while Synthetic Aperture Radar (SAR) enables damage detection even under adverse weather conditions. Dell'Acqua and Gamba (2012) demonstrated SAR's effectiveness in post-earthquake damage assessment, and Li et al. (2021) highlighted its integration with machine learning for automated classification. Complementarily, UAVs offer high-resolution, flexible mapping for rapid post-disaster surveys. Nex and Remondino (2014) emphasized the value of UAV photogrammetry in producing accurate 3D models for exposure and accessibility analysis.

IoT sensors further enhance vulnerability modeling through real-time structural health monitoring. Accelerometers, strain gauges, and GPS systems installed on infrastructure provide dynamic data during seismic events, improving early warning and maintenance strategies (Wang et al., 2018). In parallel, open data and crowdsourced platforms such as OpenStreetMap and social media streams contribute to exposure mapping and situational awareness. Goodchild and Glennon (2010) underlined the importance of volunteered geographic information (VGI) in complementing official datasets and improving spatial coverage.

Overall, integrating satellite imagery, UAV surveys, IoT monitoring, and participatory data—supported by ML/AI techniques—creates adaptive and comprehensive vulnerability models capable of responding to evolving risk scenarios.

4.2.2 Acquisition workflow

The acquisition workflow is central to data-driven vulnerability modeling, transforming heterogeneous raw data into actionable insights through four main stages: data collection, preprocessing, feature extraction, and integration into ML/AI pipelines.

Data collection draws from satellite imagery, UAV surveys, IoT sensors, and crowdsourced platforms, each presenting specific advantages and challenges. Satellite imagery ensures broad coverage but requires advanced processing to manage resolution and spectral variability (Dell'Acqua & Gamba, 2012). UAVs provide high-resolution local mapping, supported by efficient flight planning and data stitching (Nex & Remondino, 2014), while IoT sensors generate continuous structural health data that demand reliable real-time transmission systems (Wang et al., 2018).

Preprocessing ensures data quality and consistency through noise removal, georeferencing, and normalization. These steps reduce sensor errors, align datasets within common spatial frameworks, and standardize variables for effective machine learning performance. Li et al. (2021) emphasize that preprocessing significantly impacts damage detection accuracy. Feature extraction then converts raw inputs into meaningful structural and socio-economic indicators, requiring domain expertise to capture both physical fragility and social exposure (Kammouh & Cimellaro, 2019).

Finally, curated features are integrated into ML/AI pipelines, where scalable algorithms and cloud-based infrastructures support predictive modeling and real-time updates. Automated workflows and big data architectures are increasingly recognized as essential for rapid disaster response (Goodchild & Glennon, 2010; Elahi et al., 2025). Overall, a rigorous and well-structured acquisition workflow ensures that vulnerability models are robust, adaptive, and capable of supporting resilience strategies across scales.

4.2.3 Interoperability Challenges

Data interoperability represents a major obstacle in advanced vulnerability modeling frameworks. Data from satellite imagery, UAV surveys, IoT sensors, and crowdsourced platforms often differ in format, spatial resolution, temporal frequency, and semantic structure, complicating integration and potentially reducing the effectiveness of ML/AI-driven models.

A key issue concerns spatial resolution mismatches. Satellite imagery may range from 10–30 meters, UAV photogrammetry can reach centimeter-level detail, and IoT sensors provide point-based measurements with high temporal granularity. Harmonizing these datasets requires resampling and interpolation techniques that preserve essential information. Dell'Acqua and Gamba (2012) note that such mismatches can significantly affect urban damage detection accuracy.

Variations in data formats further hinder integration. Raster (e.g., GeoTIFF), vector (e.g., Shapefiles), and tabular formats (e.g., CSV, JSON) differ in structure and metadata standards. Although frameworks such as OGC standards and the INSPIRE Directive promote compatibility, inconsistencies remain, especially for volunteered geographic information (VGI), where standardized schemas are often lacking (Goodchild and Glennon, 2010).

Temporal inconsistencies add complexity, as IoT sensors provide real-time streams, while satellite and UAV data are typically batch-processed. Effective synchronization and time-series fusion are therefore essential. Wang et al. (2018) emphasize that real-time data assimilation is critical for structural health monitoring and early warning systems. Additionally, semantic and organizational differences—such as varying classification systems and data-sharing policies—limit collaboration. Linked data and semantic web technologies (Janowicz et al., 2010) offer promising solutions for machine-readable interoperability.

Overall, interoperability requires harmonizing spatial, temporal, and semantic dimensions through standardized ontologies, automated conversion tools, and cloud-based frameworks. Addressing these challenges is essential to fully unlock the potential of ML/AI-driven vulnerability models.

4.3 Data exploitation framework

The exploitation of acquired data represents a critical step in transforming raw, heterogeneous information into actionable insights for vulnerability and exposure modeling. This process involves **feature engineering**, **data fusion**, and the integration of advanced **machine learning (ML)** and **artificial intelligence (AI)** techniques. The goal is to enable predictive and prescriptive models that support decision-making in disaster preparedness and response.

4.3.1 Conceptual framework

The conceptual framework for **data exploitation in vulnerability modeling** is built upon three The conceptual framework for data exploitation is built on three interdependent pillars: **data harmonization and structuring, feature engineering, and ML/AI pipeline development**. Together, they enable the transformation of heterogeneous datasets into actionable insights for disaster risk reduction and resilience planning.

1. Data Harmonization and Structuring. This pillar focuses on integrating diverse sources—satellite imagery, UAV surveys, IoT sensors, and crowdsourced data—characterized by different spatial, temporal, and semantic properties. Harmonization aligns datasets through georeferencing, temporal synchronization, and standardized ontologies. International standards such as OGC (2025) and the INSPIRE Directive (2020) support interoperability through shared schemas and protocols. Structured, harmonized databases significantly improve preparedness and response capabilities (Okori and Obua, 2017).

2. Feature Engineering for Vulnerability Models. Harmonized data is transformed into meaningful features capturing structural, environmental, and socio-economic dimensions of vulnerability. Variables such as building typology, hazard intensity, soil type, population density, and infrastructure accessibility enhance predictive performance. Global frameworks increasingly recognize social vulnerability as a critical risk determinant (UNDRR, 2022; GFDRR, 2025). Cardoni and Cimellaro (2024) [J117] and Elahi et al. (2025) [C219] demonstrate that integrating structural and geospatial features significantly improves debris prediction and exposure assessment accuracy.

3. ML/AI Pipeline Development. The final pillar operationalizes vulnerability modeling through scalable ML/AI pipelines. Data is ingested into cloud-based infrastructures and processed using algorithms such as Gradient Boosting Machines, Convolutional Neural Networks, and Graph Neural Networks. These models support supervised vulnerability scoring and unsupervised exposure clustering. Integration with decision-support systems enhances real-time visualization and intervention prioritization, as highlighted by Devarajan (2025) and Diehra et al. (2025).

Overall, this three-pillar framework provides a scalable and interoperable approach to managing disaster risk, combining harmonized data, advanced feature engineering, and AI-driven analytics to support evidence-based resilience strategies.

4.3.2 Multi-Modal data integration

The integration of multi-modal data sources is central to modern vulnerability modeling, as disaster impacts cannot be fully captured through a single data stream. By combining remote sensing imagery, sensor data, and crowdsourced information, the exploitation process enables holistic and dynamic assessments that account for both physical fragility and social exposure, moving beyond traditional inventory-based approaches.

Remote sensing imagery provides broad spatial coverage and frequent updates for structural and terrain analysis. Optical and Synthetic Aperture Radar (SAR) data support the detection of building footprints and post-event damage patterns. Dell'Acqua and Gamba (2012) demonstrated the effectiveness of satellite imagery for post-earthquake mapping, while Li et al. (2020) highlighted the added value of UAV photogrammetry for fine-scale structural detail.

IoT sensor data complements imagery by offering real-time monitoring of structural health. Accelerometers, strain gauges, and GPS devices measure vibrations and displacements, enabling the analysis of progressive damage and cascading failures. Cimellaro et al. (2019) emphasize the importance of sensor-based resilience frameworks in urban contexts.

Crowdsourced data introduces a social dimension, enhancing situational awareness through platforms such as OpenStreetMap and social media. The concept of volunteered geographic information (VGI), introduced by Goodchild (2007), has proven critical in disaster response, including during the 2010 Haiti earthquake and subsequent flood events.

Overall, multi-modal data fusion improves predictive accuracy and decision-making by integrating physical and social risk factors. However, effective implementation requires overcoming challenges related to harmonization, interoperability, and scalability. Cloud-based geospatial platforms and AI-driven data fusion techniques provide promising solutions (Zhang et al., 2020).

4.3.3 ML/AI Techniques for exploitation

The exploitation of large-scale, heterogeneous datasets for vulnerability modeling has been greatly advanced by modern ML and AI techniques, which extract complex patterns from multi-modal sources such as satellite imagery, UAV data, IoT streams, and socio-economic datasets. Key methods include Convolutional Neural Networks (CNNs), Gradient Boosting Machines (GBM), Graph Neural Networks (GNNs), and Transfer Learning.

CNNs are central to image-based damage detection, as they learn hierarchical spatial features from high-resolution imagery. Cardoni and Cimellaro showed that CNN models accurately predict earthquake debris distribution, outperforming traditional regression approaches, while Elahi et al. confirmed their robustness in large-scale applications. Similar trends are reported by Xu et al. (2020) and Li et al. (2021) in satellite-based building damage classification.

GBM techniques, including XGBoost (Chen and Guestrin, 2016), are highly effective for structured tabular data, capturing non-linear interactions among structural, hazard, and socio-economic variables. Their scalability makes them suitable for real-time disaster response systems.

GNNs extend modeling capabilities to interconnected infrastructure networks, accounting for cascading failures and system interdependencies. Wu et al. (2021) and Zhang et al. (2022) demonstrated their relevance for resilience analysis in urban systems.

Transfer Learning addresses data scarcity by fine-tuning pre-trained models for hazard-specific tasks, reducing reliance on large labeled datasets. Foundational works by Goodfellow et al. (2016) and Krizhevsky et al. (2012) highlight its importance, particularly for rare-event scenarios.

Together, these techniques enhance predictive accuracy, scalability, and adaptability in vulnerability modeling. Evidence from Cardoni and Cimellaro, Elahi et al., and broader global research confirms the transformative impact of ML and AI on resilience science and real-time decision support.

4.3.4 Workflow and architecture

The exploitation workflow forms the backbone of data-driven vulnerability modeling, operating as a systematic and iterative pipeline that converts heterogeneous raw data into actionable insights. Each stage ensures that outputs are accurate, interpretable, and adaptable to evolving disaster contexts.

The first stage, **data ingestion**, integrates harmonized inputs from satellite imagery, UAV surveys, IoT sensors, and crowdsourced platforms. Spatial, temporal, and semantic consistency is essential to avoid downstream inconsistencies. Given the volume and velocity of geospatial and sensor data, cloud-based and distributed infrastructures are increasingly adopted to support real-time processing (Goodchild, 2018).

The second stage, **feature extraction and transformation**, converts raw observations into structured indicators for vulnerability modeling. Structural characteristics (e.g., building typology, materials, age), environmental factors (e.g., soil type, hazard intensity), and socio-economic variables (e.g., population density, accessibility) are integrated into multi-dimensional feature sets. As emphasized by Kammouh & Cimellaro (2019), this step is crucial for capturing both physical fragility and social exposure within resilience models.

The third stage, **model training and validation**, applies ML/AI techniques to identify patterns and generate predictions. Supervised learning supports vulnerability scoring, while unsupervised methods detect exposure clusters. Robust validation—through cross-validation and comparison with historical events—is essential to ensure generalizability. Cardoni & Cimellaro (2024) and Elahi et al. (2025) demonstrate that ML-based workflows significantly outperform traditional regression models in post-earthquake debris prediction.

Finally, **deployment and feedback** complete the cycle. Models are embedded in decision-support systems and continuously updated with new data, enabling adaptive learning. This iterative process reflects digital twin paradigms (Batty, 2021), where real-time data streams dynamically refine predictive models and strengthen proactive resilience planning.

4.3.5 Challenges and opportunities

The exploitation of data for vulnerability modeling involves major challenges alongside significant opportunities. **Data sparsity** is a key limitation, as disaster datasets are often incomplete or unavailable, especially in regions with limited historical records. This restricts the generalization capacity of ML models. Cimellaro et al. (2019) stress that effective resilience modeling depends on large and diverse datasets, which are rarely accessible in practice.

Interoperability presents another critical issue. Data from satellite imagery, UAV surveys, IoT sensors, and crowdsourced platforms differ in format, resolution, and semantics. Harmonization through standards such as the Open Geospatial Consortium (OGC) and the INSPIRE Directive is essential for efficient integration, as emphasized by Goodchild (2018). Without standardized frameworks, multi-modal modeling becomes error-prone.

Computational scalability is also challenging. Deep learning models require substantial processing power, particularly for large geospatial datasets, often necessitating cloud and distributed infrastructures (Zhang et al., 2020). Additionally, **uncertainty quantification** remains problematic, as many AI models function as black boxes, complicating high-stakes decision-making (Gal & Ghahramani, 2016).

Despite these barriers, promising innovations are emerging. Synthetic data generation through Generative Adversarial Networks (GANs) can alleviate data scarcity (Goodfellow et al., 2014). Federated learning enables privacy-preserving collaborative modeling without centralized data sharing (Kairouz et al., 2021), which is crucial for sensitive infrastructure information. Moreover, digital twin technologies allow dynamic virtual replicas of physical systems, supporting real-time monitoring and adaptive resilience strategies (Tao et al., 2019).

Overall, while data sparsity, interoperability, scalability, and uncertainty pose substantial challenges, advances in synthetic data, federated learning, and digital twins offer transformative pathways toward robust and scalable vulnerability modeling frameworks.

4.4 Innovative Techniques

Innovation in data exploitation is shifting vulnerability modeling from deterministic, fragility-based methods to adaptive, AI-driven frameworks that learn from dynamic, multi-modal datasets. By integrating remote sensing, ML, and AI, these systems provide predictive assessments capable of operating under uncertainty.

Deep learning is central to this transformation. Convolutional Neural Networks (CNNs) enable automated damage detection from satellite and UAV imagery, while Vision Transformers (ViTs) improve performance through attention mechanisms that capture broader urban context. Hybrid CNN–Graph Neural Network (GNN) architectures further incorporate spatial dependencies, enhancing the analysis of cascading infrastructure failures. Applications such as post-earthquake debris prediction by Cardoni & Cimellaro (2024) and Elahi et al. (2025) show that these advanced models outperform traditional regression approaches in estimating debris extent and supporting emergency logistics.

To address data scarcity, transfer learning and domain adaptation allow pre-trained models to be fine-tuned for disaster-specific applications, reducing dependence on large labeled datasets. Meanwhile, explainable AI (XAI) techniques such as SHAP and Grad-CAM improve transparency by highlighting feature importance and model attention, strengthening trust and auditability.

Synthetic data generation also mitigates limited data availability. Generative Adversarial Networks (GANs) create realistic damage scenarios, and physics-informed simulations model structural responses under varying hazards, enhancing robustness.

Another frontier is the integration of digital twins—dynamic virtual replicas updated with real-time sensor data. These systems enable predictive hazard simulations and create feedback loops between physical and virtual environments, supporting proactive resilience planning.

Collectively, these innovations form a layered ecosystem: a data layer aggregating diverse inputs, a processing layer ensuring harmonization, an AI layer applying advanced models, and a simulation layer leveraging digital twins. This architecture supports scalable, adaptive, and forward-looking vulnerability assessment frameworks.

4.5 Validation and benchmarking

Validation and benchmarking are essential to ensure that **vulnerability models** and **AI-driven damage prediction systems** are not only accurate but also reliable under diverse conditions. In the context of disaster risk management, where decisions can have life-saving implications, the credibility of predictive models depends on rigorous evaluation against **real-world data**, **synthetic scenarios**, and **standardized performance metrics**.

The complexity of vulnerability modeling stems from the **heterogeneity of input data**, which includes **remote sensing imagery**, **IoT sensor streams**, and **crowdsourced information**. Each source introduces variability in resolution, noise, and completeness. Without robust validation, models risk **overfitting to specific datasets** or failing under **out-of-distribution conditions**, as highlighted by recent studies on ML-based vulnerability detection (Ni et al., 2025). Therefore, benchmarking frameworks must incorporate **cross-validation**, **stress testing**, and **generalization checks** to guarantee operational reliability.

Benchmarking involves comparing model performance across **multiple algorithms**, **data modalities**, and **hazard scenarios**. For earthquake vulnerability assessment, metrics such as **accuracy**, **F1-score**, and **confusion matrices** are widely used (Kourehpaz & Molina Hutt, 2024). Advanced approaches also employ **Receiver Operating Characteristic (ROC) curves**, **Precision-Recall analysis**, and **calibration plots** to evaluate probabilistic predictions. [open.library.ubc.ca]

Recent literature emphasizes **multi-class classification frameworks** for damage grading, where ensemble methods like **XGBoost** and **Gradient Boosting Machines (GBM)** have achieved F1-scores exceeding **87%** for seismic damage prediction (Panda & Yadav, 2025). Similarly, deep learning models applied to post-earthquake imagery have demonstrated classification accuracies between **64% and 75%**, depending on building typology and dataset quality (Estêvão, 2024).

4.5.1 Validation against real and synthetic data

A critical challenge in disaster modeling is the **scarcity of labeled datasets**, particularly for rare extreme events. To address this, researchers increasingly rely on **synthetic data generation** and **physics-informed simulations** to augment training sets. Studies have shown that incorporating synthetic collapse scenarios can improve model sensitivity to severe damage states by up to **17%** (Kourehpaz & Molina Hutt, 2024). This approach aligns with the innovative techniques discussed in Section 6, where **Generative Adversarial Networks (GANs)** and **digital twins** play a pivotal role in creating realistic yet diverse datasets.

4.5.2 Cross-domain benchmarking

Beyond earthquake engineering, benchmarking practices from cybersecurity vulnerability detection offer valuable insights. Frameworks such as VADER and VulDetectBench propose rigorous evaluation rubrics for ML models, emphasizing interpretability and robustness under adversarial conditions (Liu et al., 2025; Sweetaroo, 2025). While these originate in software security, their principles—such as semantic-preserving transformations and stress testing for generalization—are directly applicable to disaster resilience modeling. [arxiv.org], [github.com]

4.5.3 Integration of explainable AI in validation

Modern benchmarking does not stop at accuracy metrics; it increasingly incorporates **Explainable AI (XAI)** to validate **model reasoning**. Techniques like **SHAP** and **Grad-CAM** allow evaluators to verify whether models base predictions on meaningful features rather than spurious correlations. This is particularly relevant for vulnerability models that integrate **structural attributes**, **hazard intensity measures**, and **social exposure indicators**.

4.5.4 Towards standardized benchmarks

Despite progress, the field lacks **unified benchmarking standards** for disaster vulnerability modeling. Recent reviews (Al Shafian & Hu, 2024) advocate for **open datasets**, **transparent evaluation protocols**, and **community-driven benchmarks** to accelerate innovation and ensure reproducibility. The adoption of such standards would mirror successful initiatives in other domains, fostering **trustworthy AI systems** for disaster risk reduction.

4.6 Recomandation and future work

The exploitation of data for vulnerability modeling using **innovative techniques** represents a paradigm shift in disaster risk assessment. However, the successful implementation of these methodologies requires a strategic roadmap that addresses technical, operational, and ethical dimensions. This section outlines **recommendations** for immediate actions and **future directions** to ensure scalability, interoperability, and sustainability of the proposed framework.

4.6.1 Strengthening data interoperability

One of the most pressing challenges identified throughout this deliverable is the **lack of standardized data formats and protocols**. To overcome this, future work should prioritize the adoption of **international standards** such as **OGC (Open Geospatial Consortium)** and the **INSPIRE Directive**, ensuring seamless integration of geospatial datasets across platforms. Additionally, the development of **unified ontologies** for vulnerability and exposure indicators will facilitate semantic consistency, enabling cross-domain data sharing and collaborative modeling.

4.6.2 Scaling Methodologies to EU-Wilde Applications

The techniques described in Sections 6–8 have been validated primarily at local or regional scales. Future research should focus on **scaling these methodologies to continental and global levels**, leveraging **cloud-based infrastructures** and **distributed computing frameworks**. This will allow real-time ingestion and processing of massive datasets from **satellite constellations**, **IoT sensor networks**, and **crowdsourced platforms**, supporting rapid decision-making during large-scale disasters.

4.6.3 Integration with Digital Twins and Simulation Platforms

The concept of **digital twins**, introduced in Section 6, should be expanded into a **multi-hazard simulation environment**. By coupling **physics-based models** with **AI-driven predictive analytics**, digital twins can serve as dynamic decision-support systems, enabling scenario-based planning and proactive resilience strategies. This integration will also support **continuous learning**, as real-time sensor data feeds back into the models, refining predictions and reducing uncertainty.

4.6.4 Advancing Explainable and Ethical AI

As vulnerability models increasingly rely on **black-box algorithms**, transparency becomes critical. Future work should embed **Explainable AI (XAI)** techniques into all ML/AI pipelines, ensuring that predictions are interpretable and auditable. Ethical considerations must also be addressed, particularly regarding **data privacy**, **bias mitigation**, and **accountability**. Federated learning approaches, which allow model training without centralized data storage, represent a promising avenue for privacy-preserving analytics.

4.6.5 Enhancing Robustness through Synthetic data

Data scarcity remains a major bottleneck for training high-performing models. Future research should explore **synthetic data generation** using **Generative Adversarial Networks (GANs)** and **physics-informed simulations**, as discussed in Section 6. These techniques can create realistic damage scenarios and structural response datasets, improving model generalization and resilience against rare or extreme events.

4.6.6 Establishing benchmark frameworks

To ensure comparability and reproducibility, future work should develop **benchmarking frameworks** for vulnerability modeling. These frameworks should define **standard datasets**, **evaluation metrics**, and **performance baselines** for ML/AI algorithms. Initiatives such as **data challenges** (as outlined in Task TK3.6.1) can foster innovation and collaboration among research institutions and industry stakeholders.

4.6.7 Policy and governance implications

Finally, the deployment of AI-driven vulnerability models must align with **policy frameworks** and **regulatory standards** at both national and EU levels. Future work should engage with policymakers to define **guidelines for ethical AI**, **data governance**, and **risk communication**, ensuring that technological advancements translate into actionable resilience strategies for communities.

5 Exposure database for multi-risk analyses

5.1 Database and exposure models

Exposure is one of the main factors in determining the impact associated with a risk or scenario analysis. It represents both the quantity and the quality of the elements at risk present within the investigated area; therefore, an accurate assessment of building exposure requires knowledge of the typological characteristics of the buildings located in the study area, to outline their potential response to hazardous events.

When the area under analysis is limited in extent, it is possible to aim for a **building-by-building level of detail**. Conversely, when the study area is particularly large, the time and costs required to construct a detailed exposure database increase significantly and may, in some cases, become impractical. For extensive areas, it is therefore necessary to rely on **databases providing aggregated information** over minimum spatial analysis units and to make use of **statistical correlations** between a limited set of data collected at the building scale and the corresponding information available within aggregated databases.

In the exposure models (Zuccaro and De Gregorio 2019) adopted in this study, the area investigated is discretized through a **regular spatial grid**, superimposed on the study domain. The grid is composed of square cells with a side length of **250 m × 250 m**, which represent the **minimum spatial unit of analysis**. All exposure-related information, whether derived from building-by-building surveys or from aggregated databases, is processed and aggregated at the cell level. This spatial discretization ensures consistency among heterogeneous data sources and provides a coherent framework for spatial comparison within scenario-based and multi-hazard analyses.

The building-by-building data collection is carried out using the **PLINIVS survey form** (Zuccaro et al 2021), developed by the Centro Studi PLINIVS as a standardized tool for acquiring typological information aimed at classifying building vulnerability with respect to **multi-hazard phenomena**, including geological hazards and climate-change-related processes. The PLINIVS form represents the **highest level of detail** within the exposure database construction and allows for a detailed characterization of individual buildings, integrating geometric, structural, construction-related, and functional information.

The form is structured into several sections that systematically cover the main attributes relevant to vulnerability assessment. These include building identification and spatial context, predominant use and exposure level, construction period and state of conservation, as well as key structural characteristics such as building typology, vertical and horizontal structural systems, and roof structure and geometry. Additional sections address façade characteristics, openings, non-structural elements, and indicators of regularity in plan and elevation, which are particularly relevant for seismic vulnerability evaluation.

The level of detail provided by the PLINIVS survey enables the assignment of **hazard-specific vulnerability classes** at the individual building scale, making the collected data directly applicable to the assessment of expected responses to different phenomena, such as earthquakes, volcanic ashfall, and pyroclastic flows. In this sense, the PLINIVS form is inherently conceived as a **multi-hazard-oriented tool**, supporting integrated risk assessment approaches.

Within the exposure modelling framework adopted in this study, data collected through the PLINIVS survey represent the most accurate reference level. However, due to the time and cost required for detailed field surveys, their application is generally limited to **selected areas or sample zones**. For this reason, PLINIVS-based information also plays a key role in supporting the **calibration and validation** of vulnerability inference procedures adopted when aggregated databases are used.

The **ISTAT database** (ISTAT https://www.istat.it/notizia/basi-territoriali-e-variabili-censuarie/) contains information on the building stock of the entire national territory. It provides typological information—including vertical structural system, number of storeys, and construction period—at the scale of **census zones**, which are territorial subdivisions grouping buildings with similar urban, socio-economic, and infrastructural characteristics. Each municipality may include one or more census zones, depending on the heterogeneity of its urban fabric. This classification is primarily used to define the **cadastral value** of buildings, which represents the reference value for property-related taxes and levies.

The **CARTIS database** (Zuccaro et al 2023) was developed within the framework of the **ReLUIS consortium**, as part of the WP2 CARTIS project, by approximately 30 research units distributed across the national territory since 2014. The activity, which is still ongoing, has involved data collection for about **600 Italian municipalities**, for which detailed information on building typological characteristics has been collected for **homogeneous urban sectors**. The CARTIS database is positioned as an **intermediate level** between a building-by-building data collection—characterized by long time requirements—and the ISTAT database, which covers the entire national territory but provides a lower level of detail.

5.2 Assignment of seismic vulnerability class in presence of collected data

The assignment of seismic vulnerability classes to buildings for which **building-by-building data** are available is performed using the **S.A.V.E. method** (Zuccaro and Cacace 2015), developed by the Centro Studi PLINIVS on the basis of observational data collected after seismic events from the 1976 Friuli earthquake to the most recent events.

The S.A.V.E. method is conceptually grounded in the **EMS-98 framework** (Grünthal 1998), according to which the primary seismic behaviour of a building is largely controlled by its **vertical structural typology**. However, unlike the EMS-98 approach—which assigns a vulnerability class together with an associated uncertainty range—S.A.V.E. explicitly exploits additional **building typological characteristics** to reduce the uncertainty in vulnerability class attribution.

In addition to the vertical structural typology, the method considers a set of further parameters derived from the PLINIVS survey form, including horizontal structural system, number of storeys, construction period, presence of mixed structural systems, roof typology, position of the building within an aggregate, plan regularity, and the presence of tie rods or equivalent devices. The inclusion of these parameters allows a more realistic representation of the variability in seismic response among buildings sharing the same primary structural typology.

Within the S.A.V.E. framework, a **synthetic damage parameter** is first defined for each vertical structural typology represented in the database. This parameter is estimated as the **average damage level** observed for all buildings characterized by the considered vertical typology. The base damage parameter is then **corrected** to account for the influence of the additional typological parameters. For each parameter, its influence is quantified as the mean damage level observed in buildings that share both the considered vertical typology and the parameter under analysis.

Furthermore, **correlation coefficients** are defined among the different typological parameters to weigh the contribution of each parameter according to its occurrence and its interaction with the remaining building characteristics. This approach avoids a simple linear summation of independent effects and allows the method to account for interdependence among typological features.

The **synthetic damage parameter of each building**, estimated based on all its typological characteristics, is finally compared with the ranges of average damage representative of the vulnerability classes. This comparison enables the identification of the most appropriate **seismic vulnerability class** for each building, reducing the uncertainty associated with the classification and ensuring consistency with observed damage data.

Following the seismic vulnerability classification of the damaged buildings, a **vulnerability model** was developed based on the correlation between the **assigned vulnerability class**, the **observed damage level**, and the **hazard intensity** experienced by each building. The model is derived from the analysis of post-event damage data and aims at establishing a quantitative relationship between building vulnerability and seismic demand.

Within this framework, the vulnerability model evaluates the **possible damage levels** as a function of the hazard acting on the building, consistently with the damage scale defined in the **EMS-98**, ranging from **D1 (slight damage) to D5 (destruction)**. For each vulnerability class, the model describes the expected distribution of damage levels associated with increasing hazard intensity, providing a coherent link between vulnerability classification and damage assessment.

The resulting vulnerability model therefore enables the translation of hazard scenarios into expected damage patterns at the building scale, ensuring consistency between the vulnerability classes derived through the S.A.V.E. method and the damage grades observed in real seismic events. This approach allows vulnerability assessment to be directly integrated into scenario-based and risk-oriented analyses, supporting both qualitative interpretation and quantitative impact evaluation.

5.3 Assignment of ashfall vulnerability class in the presence of collected data

Volcanic ashfall, as a hazardous phenomenon, primarily acts as an **incremental load on the building roof**, resulting from the accumulation of tephra deposits. Consequently, the **roof system** represents the main vulnerable element of the building with respect to ashfall. The increase in load induced by ash deposition is generally unlikely to compromise the overall structural functionality of the entire building; therefore, the assessment of vulnerability to ashfall specifically focuses on the characteristics and performance of the roof.

The first aspect to be considered in the vulnerability assessment is roof **geometry**. Pitched roofs favour the removal of deposited ash through gravity and runoff processes, thereby limiting the accumulation of material and preventing a significant increase in hazard. For this reason, pitched roofs are associated with **lower vulnerability classes**. As roof inclination decreases, the influence of geometric effects is reduced, and the **structural nature of the roof system** becomes the dominant factor controlling its response.

For flat roofs, vulnerability is mainly governed by the **structural typology and material quality** of the roof. Roof systems composed of excessively lightweight or poorly resistant materials exhibit a more fragile behaviour under ashfall loading. Conversely, roofs that are well connected to the structural system and behave as a structural continuum with the other load-bearing elements—such as reinforced concrete slabs—are characterized by a less vulnerable response.

Based on these considerations, **ashfall vulnerability classes** are defined by combining information on roof geometry and structural characteristics. The resulting classes range from **Class A (most vulnerable)** to **Class D (least vulnerable)**, allowing a differentiated representation of roof performance under ashfall loading conditions.

In the case of ashfall, since the expected damage mechanism is limited to the **structural failure of the roof**, the associated vulnerability model does not define a graded damage scale. Instead, damage is represented through a **binary outcome**, distinguishing between **collapsed** and **non-collapsed** roof conditions. This simplified modelling approach is consistent with the physical nature of the phenomenon and supports an effective integration of ashfall vulnerability within scenario-based multi-hazard analyses.

5.4 Assignment of pyroclastic flow vulnerability class in the presence of collected data

When dealing with **pyroclastic flows**, two fundamental factors must be considered: **lateral pressure** and **temperature**. Pyroclastic flows consist of a mixture of hot gases and pyroclastic material; when such flows can enter a building, the rapid increase in gas pressure within the enclosed space makes the hazard particularly severe. For this reason, an effective protection strategy for buildings exposed to pyroclastic flows should primarily aim at **preventing gas intrusion** into indoor environments.

In this study, the vulnerability of buildings to pyroclastic flows is evaluated by focusing on the **mechanical (collapse-related) response** of the building envelope, while **thermal effects on the structural system are not explicitly considered**. This assumption is consistent with the scope of the adopted vulnerability model and allows the assessment to concentrate on the dominant damage mechanisms associated with lateral pressure. Furthermore, considering that pyroclastic flow fronts generally reach **limited heights**, the vulnerability assessment is mainly focused on the **first and second building levels**.

The response of the lateral wall to the impact of the pyroclastic flow is evaluated by considering all the elements composing the façade, including **openings, infill walls, and structural elements**. The vulnerability assessment therefore follows a **layered approach**, starting from the most vulnerable component—the **openings and window systems**—and progressively moving towards the least vulnerable component—the **structural system**.

If openings or window systems are not sufficiently resistant to the action of the pyroclastic flow, the vulnerability class is directly assigned as the **most vulnerable**, without the need to further evaluate the performance of infill walls or structural elements. If adequate protection systems are applied to openings, the vulnerability class depends on the behaviour of the **infill walls** and is, at minimum, classified as **moderately vulnerable**. Only when the quality and resistance of the infill walls can be considered adequate does the analysis proceed to the evaluation of the **structural elements,** adopting a classification ranging from **Class A (most vulnerable)** to **Class F (least vulnerable)**.

As for ashfall, the damage model associated with pyroclastic flows does not define a graded damage scale. Instead, the damage outcome considered refers exclusively to the **collapse or non-collapse of the lateral wall**, reflecting the catastrophic nature of the phenomenon and the threshold-type behaviour of the involved damage mechanisms.

5.5 Assignment of vulnerability class in the absence of collected data

When **building-by-building survey data are not available**, the assignment of vulnerability classes necessarily relies on **statistical correlations** between robust information derived from surveyed buildings in comparable areas and **aggregated datasets** covering larger portions of the territory. In general, effective correlations can be established between **vulnerability classes and construction periods**, which represent one of the most reliable and widely available parameters in large-scale building inventories.

In this study, such correlations are exploited through the **B.I.N.C. model**. (Cacace et al 2018) As a representative example, the model is here applied to **seismic vulnerability classes** derived from the **S.A.V.E. method**, since earthquakes are among the hazards that may affect **very large areas at the national scale**, making building-by-building surveys often impractical. Conversely, volcanic phenomena are typically characterized by a more **spatially confined extent**, which generally allows the adoption of survey-based approaches using collected data. For this reason, the B.I.N.C. approach is primarily intended to support large-scale seismic vulnerability assessments.

The B.I.N.C. model exploits information obtained from the S.A.V.E. method and establishes a correlation between the **frequency of occurrence of each vulnerability class as a function of construction age** and the **building stock characteristics** reported in the ISTAT database. In this way, vulnerability class distributions inferred from surveyed buildings are statistically transferred to areas where only aggregated information is available.

ISTAT building data are originally provided at the scale of **census sections**, whereas the reference spatial unit adopted in this study is the **250 m × 250 m grid cell**. Since a census section may intersect multiple grid cells, a spatial redistribution procedure is required. To this purpose, **zones** are defined as the areas resulting from the intersection between census sections and the regular grid (Figure 1).

For each census section, the total number of buildings is first redistributed among the corresponding zones. When surveyed buildings are available within a zone, the vulnerability class distribution obtained through the S.A.V.E. method is preserved. For the remaining, non-surveyed buildings, vulnerability classes are inferred using the class-frequency relationships derived from S.A.V.E., ensuring consistency between observed and inferred data.

The number of buildings of vulnerability class k assigned to zone i of census section j is computed according to the following rules:

$$E_{ij}^{k} = \begin{cases} E_{ij}^{k,R} & \text{when: } E_{j}^{ISTAT}/E_{j}^{R} \leq 1 \\ E_{ij}^{k,R} + E_{ij}^{k,\bar{R}} = E_{ij}^{k,R} + E_{j}^{k}/E_{j}^{ISTAT} \cdot (E_{ij} - E_{ij}^{R}) & \text{when: } E_{j}^{ISTAT}/E_{j}^{R} > 1 \end{cases} \quad (1)$$

The total number of buildings of vulnerability class k within a grid cell c is then obtained by summing the contributions of all zones belonging to that cell:

$$E_{c}^{k} = \sum_{i=1}^{n} E_{ij}^{k} \quad (2)$$

where:

- c cell;
- j census section;
- i zone, intersection of the reference grid and census section;
- k vulnerability class (k = A, B, C, D);
- n number of zones constituting cell I;
- E_{ISTATj} number of buildings in census section j;
- E_{kj} number of buildings of census section j; of vulnerability class k (BINC);
- E_{Rj} number of buildings of census section j; surveyed;
- $E_{ki,j}$ number of buildings in zone i of census section j; of vulnerability class k;
- $E_{k,Rij}$ number of buildings detected of zone i of census section j; of vulnerability class k (S.A.V.E.);
- $E_{k,Ri,j}$ number of undetected buildings of zone i of census section j; of vulnerability class k;
- E_{kc} number of buildings in cell c of vulnerability class k.

Through this procedure, the B.I.N.C. model enables a **spatially coherent reconstruction of vulnerability class distributions** at the grid-cell scale, even in the absence of detailed survey data. While this approach introduces a higher level of epistemic uncertainty compared to survey-based assessments, it provides a **scalable and operational solution** for vulnerability modelling over large areas, ensuring consistency with observed vulnerability patterns derived from S.A.V.E. and representativeness at the territorial scale.

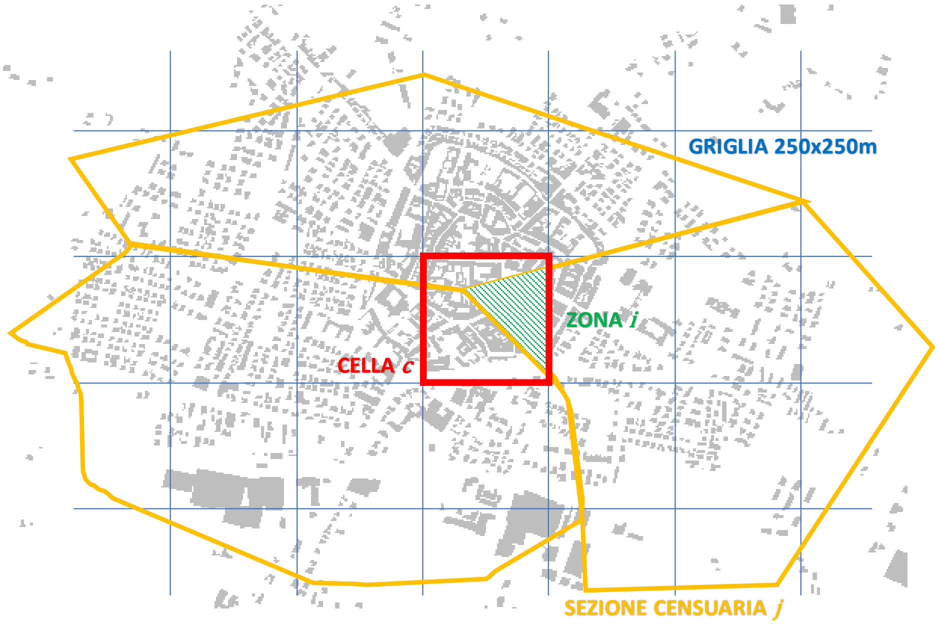

Figure 1. Illustrative representation of the 'zones' (green), defined as the areas of intersection between the ISTAT census sections (yellow) and the 250 x 250m cells (red) of the model's reference grid (blue)

5.6 Vulnerability index

The vulnerability index adopted in this study is conceived as a **synthetic measure** aimed at integrating, within a single metric, information related to the **exposure of elements at risk** and their **hazard-specific vulnerability**.

Vulnerability expresses the response capacity of a given building typology to a specific natural phenomenon and therefore represents an intrinsic property of the building, dependent on its structural, geometric, and construction characteristics. Exposure, on the other hand, is defined as the quantitative and qualitative distribution of elements at risk over the territory; within the concept of "quality" are included those characteristics that influence the building response to the event and, consequently, its vulnerability.

The main objective of the index is not to provide a direct quantitative estimate of expected damage, but rather to enable a **qualitative and visual comparison among different portions of the territory**, allowing the rapid identification of areas where, under the same hazard conditions, a more severe impact can reasonably be expected. In this sense, the index is intended as a tool to support the spatial interpretation of results, rather than as an absolute measure of loss.

The index is calculated at the **territorial cell scale**, consistently with the spatial framework adopted in the multi-hazard analysis models. For each cell, the index combines:

- exposure characteristics, in terms of building typology, density, and use;
- vulnerability classes assigned to the exposed elements, defined according to criteria specific to each considered phenomenon (seismic, ashfall, pyroclastic flows).

Operationally, the vulnerability index is defined as the **sum of the products** between the number of buildings belonging to each vulnerability class and the **weight assigned to that class**, normalized with respect to the maximum number of buildings present in the most populated cell within the study area. In mathematical form, the index can be expressed as:

$$I_V = \frac{\sum_{i=1}^{n} N_i \cdot w_i}{N_{\max}} \tag{3}$$

where N_i represents the number of buildings belonging to vulnerability class i within the cell, w_i is the weight associated with class i, defined as a function of the expected response to the considered phenomenon, and $N_{\max}$ is the maximum number of buildings observed in the most populated cell, used as a normalization factor.

In this framework, the index represents a **relative measure**, useful for ranking cells according to their potential contribution to overall damage. Cells characterized by a high concentration of exposed elements and a predominance of higher vulnerability classes will exhibit larger index values, indicating greater relative criticality compared to other areas subject to the same hazard scenario.

A key feature of the vulnerability index is its **comparative nature**: under equal hazard conditions, differences in index values reflect exclusively variations in the combination of exposure and vulnerability. This enables an immediate reading of thematic maps, supporting result interpretation and the identification of intervention priorities, both in planning and emergency management phases.

Finally, the vulnerability index is conceived as a **flexible tool**, easily adaptable to different territorial contexts and levels of data detail. It does not replace individual vulnerability classes or fragility curves adopted for the various hazards, but rather integrates them into a synthetic measure, functional to spatial analysis and to comparisons among multi-hazard scenarios.

5.7 Case study: Campi Flegrei

The collected data were reviewed by PLINIVS both during field surveys and after weekly data imports. Using the PLINIVS survey form, a seismic vulnerability class was assigned to 9,078 ordinary private buildings (residential and/or service use) according to the EMS-98 classification, applying the first-level SAVE methodology. Approximately 48% of the buildings fall within the less vulnerable classes (C–D), while 14% belong to the most vulnerable class (A).

The SAVE procedure is not applicable to 55 timber buildings (37 residential), for which an ad hoc assessment will be required (expert judgment suggests a vulnerability class between B and C). In addition, 352 buildings could not be classified due to missing structural information; overall, 407 ordinary buildings remain unclassified, of which 24% were not accessible. Cells containing classified ordinary buildings are 442 out of 682 total cells; the remaining cells are either undeveloped or contain no classified ordinary buildings.

In DV 3.3.4 the associated maps for the vulnerability index associated with the area are also represented.

	Vulnerability Class				**N.C.***			
	A	**B**	**C**	**D**	**Timber**	**NO V.S.****	**Tot.**	**TOT.**
N° buildings	1.258	3.030	892	3.491	55	352	**407**	**9.078**
% buildings	13,9	33,4	9,8	38,5	0,6	3,9	**4,5**	**100**

*N.C. = Building not classified by SAVE procedure; ** NO V.S. = No info on vertical structure

Table 1. Distributions of Vulnerability Classes (A-D) of ordinary buildings, assigned on the basis of the data collected with the PLINIVS Form, in accordance with the SAVE procedure.

6 Conclusions

This deliverable has presented a comprehensive framework for the collection, integration, and exploitation of heterogeneous data sources aimed at feeding advanced vulnerability models for multi-risk assessment under changing climate conditions. Within the scope of WP6 and Task T6.1, the work has addressed the full data value chain — from acquisition methodologies and interoperability challenges to the implementation of ML/AI-driven exploitation strategies and validation protocols.

The proposed data exploitation framework demonstrates how multi-modal information — including remote sensing data, in-situ surveys, exposure databases, and synthetic datasets — can be systematically integrated to support vulnerability classification for multiple hazards, including seismic events, ashfall, and pyroclastic flows. Particular attention has been devoted to ensuring methodological robustness both in contexts where detailed building-level data are available and in scenarios characterized by partial or missing information. In this regard, the definition of vulnerability indices and classification procedures represents a key contribution toward scalable and transferable multi-risk applications.

The integration of machine learning techniques, including multimodal and explainable AI approaches, has shown significant potential in improving predictive capabilities, enhancing debris estimation, and supporting vulnerability assessment processes. At the same time, the document highlights the importance of interpretability, benchmarking, and cross-domain validation to ensure transparency, reliability, and reproducibility of results. The inclusion of explainable AI components within the validation phase strengthens the credibility of the proposed methodologies and facilitates their adoption in operational and policy-making contexts.

The case study of Campi Flegrei has provided a meaningful application scenario, demonstrating the feasibility of the proposed workflow in a complex multi-hazard environment characterized by high exposure and evolving volcanic risk. This application confirms the adaptability of the framework to real-world conditions and its potential contribution to territorial resilience planning.

From a broader perspective, this work contributes to the advancement of standardized methodologies for vulnerability assessment, fostering interoperability between databases, alignment with European-scale applications, and future integration with digital twins and simulation platforms. The emphasis on synthetic data generation, benchmarking frameworks, and ethical AI further positions the proposed approach within the evolving landscape of resilient, data-driven risk governance.

In conclusion, DV3.6.1 establishes a structured and innovative methodological foundation for exploiting heterogeneous data to enhance vulnerability modeling in multi-risk scenarios. The outcomes achieved lay the groundwork for future developments aimed at operational deployment, scaling across European contexts, and continuous refinement of AI-driven vulnerability assessment tools in support of resilient communities under a changing climate.

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