



Università
di Catania

PHD PROGRAM “DEFENSE AGAINST NATURAL RISKS AND
ECOLOGICAL TRANSITION OF THE BUILT ENVIRONMENT” — XXXVIII CYCLE

PhD Thesis Title:

Proposal for Micro-Zoning Seismic Risk Map Protocol for Safety Evaluation of Structures



PhD Candidate:	Eng. Habib Imani
Coordinator:	Prof. Massimo Cuomo
Supervisor:	Prof. Vincenzo Minutolo
Co-Supervisors:	Prof. Salvatore Losco; Prof. Renato Zona
Co-Advisor:	Prof. Henning Wessels

2022/2025

Abstract

Italy faces a high seismic risk, which makes the assessment of structural vulnerability an urgent priority. This is particularly critical for *reinforced concrete* (**RC**) buildings, which represent a large share of the urban stock. Many of these structures remain fragile, not only due to age but also because of geometric irregularities and construction practices that often fell short of modern standards, despite advances in codes and regulations.

This doctoral thesis presents a two-stage workflow for assessing the seismic vulnerability of **RC** buildings at the urban scale. The approach combines mechanics-based analysis with data-driven prediction, generating results that can be directly transferred into *geographic information systems* (**GIS**) for vulnerability mapping.

In the first stage, geometric and qualitative attributes—such as plan dimensions, number of floors, vertical regularity, age, and maintenance—are gathered from public sources (Google Maps, *quantum geographic information system* (**QGIS**)). Each building is modeled as a *virtual twin* (**VT**) and analyzed through *finite element limit analysis* (**FELA**), following Melan’s lower-bound theorem, to obtain the *collapse coefficient* (**CC**) as an indicator of mechanical capacity. This measure is then combined with qualitative modifiers to derive a vulnerability score V , which is compared with established macroseismic models (e.g., the European Macroseismic Scale 1998 [EMS-98], AEDES) expressed in terms of seismic intensity I and ductility index μ_{Δ} . The consistency of this comparison confirms the reliability and practical value of the mechanics-based method.

The second stage addresses the computational cost, supervised *machine learning* (**ML**) models were trained on 106 fully analyzed buildings and then applied to the full RC stock (347 buildings), achieving accuracy comparable to mechanics-based results, while requiring much less computational time.

Overall, the proposed method offers a practical and scalable framework for assessing seismic vulnerability and planning urban resilience. By combining detailed mechanical insight with fast predictive tools, it offers civil protection authorities, engineers, and local administrations a reliable basis for decision-making.

Sommario

L'Italia presenta un'elevata pericolosità sismica e, di conseguenza, la valutazione della vulnerabilità strutturale dovrebbe costituire una priorità, considerando la predominanza di edifici in calcestruzzo armato (CA), che rappresentano una quota significativa del patrimonio edilizio nelle aree urbane. A causa della vetustà, delle irregolarità geometriche e della scarsa qualità costruttiva, numerose strutture in CA risultano ancora vulnerabili nonostante i miglioramenti introdotti nella classificazione sismica e nella normativa edilizia nel corso del tempo.

La presente tesi di dottorato propone un approccio ibrido articolato in due fasi per la valutazione della vulnerabilità sismica e la microzonazione degli edifici in CA. La metodologia sviluppata integra il calcolo meccanico con la previsione basata su dati, allo scopo di garantire affidabilità e scalabilità nella stima della vulnerabilità a livello urbano.

Nella prima fase, i dati geometrici e qualitativi specifici di ciascun edificio — come le dimensioni in pianta, il numero di piani, la regolarità in elevazione, l'età e lo stato di manutenzione — vengono estratti tramite strumenti accessibili come Google Maps e **QGIS**. Ogni struttura è successivamente modellata in ANSYS e analizzata in MATLAB secondo il teorema del limite inferiore di Melan, ottenendo un Coefficiente di Collasso (CC) rappresentativo della sua capacità meccanica. Tale coefficiente viene modificato mediante fattori qualitativi per ottenere un Indice di Vulnerabilità (V), la cui validazione avviene attraverso il confronto con modelli macrosismici consolidati, utilizzando come parametri di ingresso l'intensità sismica e l'indice di duttilità. L'accordo ottenuto conferma l'affidabilità dell'approccio basato su calcoli meccanici.

Nella seconda fase, i modelli di apprendimento supervisionato sono **addestrati su 106 edifici analizzati integralmente e applicati all'intero stock in CA (347 edifici)**, con accuratezza paragonabile ai risultati meccanici e tempi di calcolo ridotti.

Il metodo proposto fornisce uno strumento innovativo, efficiente e adattabile per la valutazione del rischio sismico e la pianificazione della resilienza urbana. Colmando il divario tra simulazioni dettagliate e applicazioni su larga scala, esso offre un supporto concreto per le autorità di protezione civile, gli ingegneri e i funzionari comunali.

Keywords

- Seismic Vulnerability
- Earthquake Resilience
- Reinforced Concrete Buildings
- Micro-zoning Procedure
- Structural Safety Assessment
- Finite Element
- Limit Analysis
- Virtual Twin
- Machine Learning

INDEX

Contents

List of Acronyms	12
1 Introduction	13
1.1 Background	13
1.2 Motivation and Problem Statement	14
1.3 Objectives of the Research	15
1.4 Methodological Approach	16
1.5 Scientific and Technical Innovations	17
1.6 State of the Art	18
1.7 Review of Similar Research	19
1.7.1 Macroseismic Models	19
1.7.2 Statistical and Machine Learning Approaches	19
1.8 Structure of the Thesis	20
2 Theoretical Background	21
2.1 Basis and Fundamentals of Finite Elements	21
2.1.1 Origin and Principle of FEM	21
2.1.2 Discretization, Shape Functions, and Stiffness Matrices	21
2.1.3 Application to Continuum Mechanics and RC Structures	22
2.1.4 Relevance in Modeling Structural Collapse	22
2.2 Limit Analysis	23
2.2.1 Fundamentals of Plasticity Theory	23
2.2.2 Limit Analysis Theorems	23
2.2.3 Lower Bound Formulation and Optimization	24
2.2.4 Application to Reinforced Concrete (RC) Structures and Collapse Assessment	26
2.3 Seismic Vulnerability and Background	27
2.3.1 Definition of Seismic Vulnerability	27
2.3.2 Background and Historical Methods	28
2.3.3 Parameters Influencing Vulnerability	29
2.3.4 Urban-Scale Assessment Techniques	31
2.3.5 Limitations of Traditional Methods	32

2.3.6	Advances in Seismic Vulnerability Assessment Methods	33
2.3.7	Country-Specific Advances and Key Initiatives in Europe	36
2.4	Definition of Collapse Load and Collapse Coefficient	39
2.4.1	Collapse Load	39
2.4.2	Elastic Threshold vs. Ultimate Capacity	39
2.4.3	Definition and Role of the Collapse Coefficient	39
2.4.4	Interpretation and Implications in Structural Assessment	39
2.5	Integrated Numerical–Observational Approach for Assessing Reinforced Concrete Buildings	40
2.5.1	Rationale for the Hybrid Approach	40
2.5.2	Sources of Observational Data	41
2.5.3	Parameters Extracted from Visual Observation	41
2.5.4	Numerical Modeling and Integration	43
2.5.5	Synthesis: Hybrid Workflow	45
3	Methodology	49
3.1	Collecting Urban Building Data Using Available Tools	49
3.2	Definition of Structural Types, Selection of Suitable Data, and Geometric Pre- processing	49
3.3	Modeling in ANSYS and MATLAB–GRIDWORK	51
3.3.1	Geometric Preprocessing in ANSYS	51
3.3.2	Model Transfer to MATLAB and the GRIDWORK Framework	51
3.4	Calculation of the Collapse Coefficient for Each Virtual Twin	52
3.5	Definition of the Safety Index by Combining Qualitative Factors	53
3.6	Final Definition of Safety Classification and Vulnerability Levels	54
3.6.1	SafeScore Classification	54
3.6.2	Final Vulnerability Index	55
3.6.3	Basis and Use	55
4	Vulnerability Classification and Mapping	56
4.1	Aim: Microzoning of the Built Environment	56
4.1.1	Review of Similar Methods and Frameworks	58
4.2	Method: Finite Element Limit Analysis (FELA)	59
4.2.1	Lower-Bound Formulation	59
4.2.2	Polyhedral Yield Domain	59
4.2.3	Determination of the Collapse Coefficient and its Relation to Vulnerability	60
4.2.4	Z-FEM: Key Advantages	60
4.3	Four-Level Vulnerability Classification	61
4.3.1	Practical Example of the Classification	61
4.4	Display of Results in QGIS (Seismic microzonation Map)	64
4.4.1	Data import and attribute join.	64

4.4.2	Symbology and categorical mapping.	64
4.4.3	Map composition and export.	64
4.5	Statistical Analysis of Vulnerability Results	65
4.5.1	Correlation between collapse coefficient and number of floors.	67
4.5.2	Interpretation and implications.	69
5	Dataset Construction	70
5.1	General Objective of Dataset Construction	71
5.2	Data Sources and Sample Categorization	71
5.3	Creation of Virtual Twins	71
5.4	Feature Categorization	74
5.5	File Structure and Preprocessing	74
5.6	Validity and Diversity of Data	74
5.7	Advantages of Synthetic Data	74
5.8	Storage and Final Format	75
6	Analysis of Results and Vulnerability Classification	76
6.1	Introduction and Objectives of Results Analysis	76
6.2	Criteria for Vulnerability Level Classification	76
6.3	Statistical Analysis of Seismic Vulnerability Classification Results	77
6.4	Spatial Analysis and Vulnerability Mapping	78
6.5	Statistical Analysis of Factors Influencing Seismic Vulnerability	79
7	Validation	81
7.1	Introduction to the Macroseismic Model by Ferreira et al. (2020)	81
7.2	Introduction to the Macroseismic Model by Lagomarsino & Giovinazzi (2006)	82
7.3	Comparative Analysis of μ_D Between the Proposed Model and References	82
7.4	Deviation, Conceptual and Numerical Fit Analysis	84
8	Machine Learning for Urban-Scale Seismic Vulnerability Prediction	86
8.1	Rationale for Using ML at Urban Scale	86
8.2	Data and Clustering Strategy	86
8.3	Machine-Learning Algorithms	87
8.4	Training and Model Selection	88
8.5	Outlook: Integrating Virtual Twins with Real-World Data	90
8.6	Summary	90
9	Applications and Discussion	91
9.1	Urban-scale Applications and Decision-making	91
9.2	Supporting Emergency Management	91
9.3	Comparison with Existing Methods	92
9.4	Strengths and Innovations	93

9.5	Limitations and Challenges	93
9.6	Future Perspectives	94
9.7	Chapter Summary	95
10	Conclusions and Future Work	96
10.1	Summary of Findings	96
10.2	Contributions	96
10.3	Limitations	97
10.4	Targeted Out-of-sample Validation	97
10.5	Future Work	98
10.6	Closing Remarks	98
	Acknowledgments	100
	Appendix A: Useful Databases and Open-Source Resources for Seismic Hazard and Vulnerability Assessment	101
	Appendix B: Complete data set of the structural models analyzed	103

List of Figures

2.1	Example of complex plans excluded from the dataset. Large internal openings and irregular layouts, often designed for increased daylight or architectural space, introduce significant modeling complexity and were therefore omitted.	43
2.2	Process diagram of the hybrid workflow.	47
3.1	Flowchart of the data preprocessing and structural classification process.	50
4.1	Seismic micro-zoning map of the study area. <i>Reproduced from Zona et al. (2025).</i>	57
4.2	Schematic polyhedral approximation of the yield surface in stress space.	60
4.3	Final seismic vulnerability classification map for the central area of Avellino. Buildings are classified from <i>Safe</i> (green) to <i>Highly Vulnerable</i> (black). Buildings outside the study scope are shown with a hatched fill to visually distinguish surveyed areas from data-sparse zones; the red polyline highlights the main street in the area.	65
4.4	Distribution of buildings by vulnerability class (counts).	66
4.5	Share of buildings by vulnerability class (percentages).	66
4.6	Histogram of the vulnerability index V (bin width 0.1).	67
4.7	Scatter of CC versus number of floors with OLS trend line.	68
4.8	Distribution of CC by floor count (boxplots without outliers).	68
4.9	Mean CC versus floor count with 95% confidence intervals.	69
5.1	3D view of a VT in the preprocessing stage.	72
5.2	3D view of a VT with 40 cm $\times$ 60 cm section dimensions.	73
5.3	3D view of a VT in MATLAB analysis stage. Example: <code>Telaio_3_2_3_5_5</code>	73
6.1	Distribution of Seismic Vulnerability Levels for All RC Buildings ($N = 347$) . . .	78
6.2	Seismic Vulnerability Microzonation of RC Buildings in the Urban Area of Avellino	79
6.3	Role of qualitative factors in determining the seismic vulnerability level of structures.	80
7.1	Comparison of mean damage grade μ_D between the proposed model and Ferreira et al. (2020). Both show similar increasing trends with intensity; the proposed model is slightly more conservative.	83
7.2	Comparison of mean damage grade μ_D between the proposed model and Lago-marsino & Giovinazzi (2006). The overall increasing trend is preserved, while the proposed model produces lower μ_D values.	84

8.1	Predicted vs. Actual CC . The 45° line indicates perfect agreement.	89
8.2	Clustering-based workflow for ML prediction of CC	89
10.1	Parity plot of predicted vs. actual CC on the 20 audited buildings.	98

List of Tables

3.1	Qualitative coefficients assigned to observed parameters.	54
3.2	SafeScore (SS) classification levels.	54
3.3	Final seismic vulnerability levels (V) with color coding.	55
4.1	Comparison between the present method and similar methods/frameworks . . .	58
4.2	Summary of the four-level seismic vulnerability classification	61
4.3	Sample of the real dataset used in this study.	63
4.4	Distribution of buildings by vulnerability class.	66
5.1	Accounting of buildings and virtual twins used in this thesis.	70
5.2	Sample validated structural model data (partial list).	75
7.1	Comparison metrics of the proposed method with Ferreira and Lagomarsino. . .	85
8.1	Algorithm overview (qualitative).	87
8.2	Evaluation on the baseline 106 labeled buildings (initial pipeline).	88
9.1	Comparison of seismic vulnerability assessment approaches.	92
9.2	Key limitations and mitigation paths.	94
9.3	Future directions and expected impact.	95
10.1	Targeted 20-sample audit by prediction stratum (errors on CC).	97
3	Complete dataset of 106 analysed structural models.	103
4	Description of each parameter used in the dataset	105

List of Acronyms

Abbreviation	Term
RC	Reinforced Concrete
VT	Virtual Twin
FELA	Finite Element Limit Analysis
ML	Machine Learning
CC	Collapse Coefficient
FEM	Finite Element Method
GIS	Geographic Information Systems

Chapter 1

Introduction

1.1 Background

Italy has a long history of earthquakes. After the devastating Messina earthquake of 1908, Italy's first official seismic regulations were approved in 1909. The first mandatory seismic zoning law covering the national territory was Law No. 64 in 1974. This was the beginning of a formal and mandatory state classification based on scientific criteria. Since then, the Italian seismic classification has undergone major updates, most notably with the development of the MPS04 model in 2004 and the approval of new national building codes after the L'Aquila earthquake in 2009 (Stucchi et al., 2011).

Since then, a comprehensive national environmental classification was created in 2008, which established the precise nature of earthquakes. It should be noted that this category only includes areas with low earthquake potential (Meletti et al., 2014). Even relatively low-magnitude seismic events demonstrate the ability to cause significant damage. This underscores the critical importance of understanding the vulnerability of Italian buildings. This continued vulnerability is due to the unpredictable nature of earthquake events, and prioritizing prevention emerges as the main approach to guaranteeing safety and civil protection. Therefore, discussing prevention in this context means understanding the current risks to the built environment and taking effective measures to reduce the risks (Dolce et al., 2021).

Given Italy's significant seismic history and the widespread vulnerability of the built environment worldwide, assessing the risk and vulnerability of buildings in earthquake engineering remains a central concern. A proper understanding of the levels of seismic risk is critical to reducing earthquake-related damage through preventive strategies and effective emergency planning. Seismic risk is typically described as a function of hazard, vulnerability, and exposure, which together determine the potential consequences of a seismic event (CPD, 2024). In certain situations, particularly in mountainous or unstable terrain, it is also crucial to evaluate secondary hazards such as landslides, which may be triggered by earthquakes and significantly contribute to structural damage (Ferreira et al., 2020). The vulnerability of buildings, in particular, refers

to their capacity to withstand seismic actions of a given intensity and is a key component in determining risk levels (Losco et al., 2012)(Losco & Macchia, 2016).

On the other hand, empirical methods evaluate the distribution of damage observed after past earthquakes, relating it to various building typologies and macroseismic intensity levels (Ferreira, 2010). Analytical approaches, in contrast, involve more computational effort and require detailed structural modeling, which depends on representative assumptions about mechanical properties and geometric configurations specific to each building class. Heuristic methods rely on expert judgment to estimate the seismic vulnerability of buildings based on observable characteristics (Vicente et al., 2014). Several simplified approaches for the evaluation of seismic vulnerability have also been developed. These include the P25 scoring method (Bal et al., 2008), ATC-21's "Rapid Visual Screening of Buildings for Potential Seismic Hazards" (FEMA, 2017), and other methods proposed by GNDT II (GNDT-SSN, 1994; Hirose et al., 1992; Rai, 2008; Yakut et al., 2013).

1.2 Motivation and Problem Statement

The development of rapid classification methods for earthquake risk has led to significant interest in simplified vulnerability assessment procedures. One such method is outlined in Appendix A of the Guidelines for Classifying Earthquake Risk in Buildings Department Decree No. 124, 2020 (Infrastructures, 2020), which provides a basic seismic risk estimation technique specifically tailored for masonry buildings (Picchi, 2016). This method is not used in the current study, as it was specifically developed for masonry buildings and is primarily aimed at estimating economic costs.

Across Europe, approximately 30% of buildings feature a *reinforced concrete* (**RC**) structural system. In Italy, due to the considerable age of the urban fabric and the high proportion of buildings without seismic design provisions, it is estimated that more than 70% of residential buildings were constructed before 1981. These older constructions are often considered vulnerable because of inadequate seismic detailing (Crowley et al., 2020); (ReLUIS Consortium, 2021). Instead, this study focuses on **RC** buildings in the city area. These structures often lie outside historic masonry centers but still require a strong risk assessment. A new classification method is proposed that builds on earlier efforts by the research team, including a simplified abacus developed by the author and a PhD student (Tataro, 2022). The term 'abacus' here refers to tabular visual tools for decision-making. This numerical method assesses structural behavior and is going to be improved through *machine learning* (**ML**) techniques.

Other literature suggests two major strategies for seismic vulnerability assessment (Zuccaro & Cacace, 2015): empirical methods, which rely on post-earthquake damage observations (Braga et al., 1982; Dolce & Ponzio, 2002; Spence et al., 2005), and mechanical methods, which include analytical or numerical assessment (Dolce et al., 2006; Frascadore et al., 2015). These are not directly used in this research but serve as the theoretical foundation supporting the study's process.

In future phases, novelties in Structural Health Monitoring (SHM), including technologies like distributed optical fiber sensors (DOFS) or other innovations, may contribute to the development of vulnerability assessment systems. While this is not part of the current implementation, it represents a promising avenue for complementing mechanical-based risk classification with real-time observational data (Plessi et al., 2007).

1.3 Objectives of the Research

Classifying individual buildings by seismic risk—key to understanding the potential impact of future earthquakes—is based on their seismic resistance characteristics. These characteristics are determined by the geometry and mechanical properties of the materials used in construction. This work seeks to establish qualitative standards derived from site inspections, surveys, and construction data, along with regulatory references relevant to the construction period. These qualitative standards will serve as the basis for deriving quantitative data regarding mechanical properties necessary for simplified analyses. The data and results obtained from surveys aim to construct typical numerical models that can undergo fast and reliable strength and resistance analysis.

The project aims to evaluate seismic risk on existing buildings and develop new identification and classification approaches specifically tailored for **RC** buildings, which are parts of Italy’s cultural heritage to be safeguarded. Seismic risk in Italy is underscored by the frequency of seismic events, even of minor magnitudes. Therefore, a systematic approach to structural Identifying, particularly through detailed classification of existing buildings, especially those constructed with **RC**, is imperative. This involves identifying seismic risk for decision-making purposes, which entails identifying the parameters that characterize it for risk assessment and representation. Seismic hazards manifest themselves through the possible consequences of future earthquakes, including economic and social impacts.

Although this research does not primarily focus on historical structures, but particular attention is given to buildings constructed in the post-Second World War period, mainly those made of **RC**. These buildings usually have initial structural patterns that have not fully founded the concepts of seismic design or were constructed according to the old norms that no longer reflect the current knowledge in structural engineering. Understanding its seismic performance is considered a secondary objective of the study, as these structures constitute a significant portion of the environment built in many areas of the city and remain widely not evaluated for seismic vulnerability.

In line with the “Guidelines for the Seismic Risk Classification of Constructions” (Ministerial Decree No. 58, 2017) (IMIT, 2017), the research also aims to contribute to the development and testing of simplified tools that may support the estimation of the CRS index at the territorial scale. While not delivering a complete forecasting framework, the project introduces strategies that help define performance levels through simplified parameters derived from building observations and measurements. These exploratory efforts are intended to align the

broader goal of improving the scalability and accessibility of national classification structures.

1.4 Methodological Approach

Limit analysis is a branch of structural mechanics that evaluates the safety of structures without requiring a full understanding of their exact nonlinear response to environmental loads or conditions. Instead of focusing on the exact magnitudes of applied loads, this approach depends on the evaluation of internal stress distributions and ensures structural balance and compatibility within predefined limit states (W.-F. Chen et al., 2007).

The feasibility of large-scale seismic vulnerability assessment for **RC** buildings has been advanced by integrating recent developments in seismic risk modeling and structural performance analysis. Initial analytical methods were usually based on nonlinear step-by-step simulations of prototype structures subject to representative seismic inputs. However, these analyses are really difficult, leading researchers to look for simplified but reliable alternatives. This doctoral thesis proposes a methodology that characterizes the nonlinear behavior of various building stocks through a simplified pushover analysis based on limit analysis principles (Chopra & Goel, 2002).

To address this, a simplified pushover analysis can be performed using static methods derived from the limit analysis techniques. This approach eliminates the need for computational step-by-step procedures and avoids dependence on predefined collapse mechanisms, which are usually difficult to model and may result in overestimation of structural collapse capacity. Without limitation to specific failure patterns, static limit analysis can be applied to structures with diverse geometrical and mechanical properties. The project presents a method that uses limit analysis to develop structural capacity curves based on essential parameters—such as building geometry, material properties, and estimated loads—collected from qualitative and quantitative surveys. These datasets form a simplified modeling basis and contribute to establishing a practical protocol for use by decision-makers.

After characterization at the building level, the research proceeds to a contextual phase in which representative structural types are grouped based on construction features, documented data, and building regulations applicable at the time of construction. Although this is not a full urban typological classification, the grouping supports the identification of structural profiles with similar seismic risk.

The final step involves the production of illustrative seismic micro-zoning maps using typical structural models. These maps are generated through a qualitative classification of the vulnerability of construction, which captures observed and potential damage scenarios (Zuccaro & Cacace, 2015). The objective is not exhaustive territorial mapping, but to demonstrate the practical application of the proposed methodology in identifying high-risk areas and supporting risk reduction planning.

Although social or demographic indicators are not explicitly addressed, this research is firmly focused on assessing the seismic risk from a structural engineering perspective. The results are

spatially visualized using *quantum geographic information system* (**QGIS**), which allows the integration of input data and simulation outputs into the city maps. This spatial representation helps identify danger zones and supports decision makers in planning targeted interventions.

In this approach, the first phase depends on mechanical modeling and numerical analysis to evaluate the seismic behavior of individual buildings. The second phase is based on the results of the first, incorporating supervised **ML** techniques. These algorithms are trained using mechanical analysis data to predict seismic vulnerability based on observable structural characteristics. This significantly improves the speed, scalability, and cost-efficiency of the evaluation, especially when applied on the urban scale.

1.5 Scientific and Technical Innovations

One of the modern approaches to structural health monitoring involves the use of NSHT sensors (New Smart Hybrid Transducer), which enable the accurate and continuous recording of data on the condition of structures and infrastructures. These datasets provide a basis for analyzing changes in structural performance over time, thereby improving vulnerability monitoring, intervention planning, and risk reduction against natural hazards. Although such sensors were not applied in the present project, related studies—such as (Minutolo et al., 2020)—play an important role in expanding field data repositories and integrating them with numerical modeling.

The study is based on various foundations, including building construction, structural components, and territory. It is very important to know the features of the infrastructure being studied, how well it is maintained, and the shape and layout of the structures to recognize common types and their quality. Qualitative information gathering is complemented by quantitative investigations facilitated by literature case studies and field data. One of the key scientific contributions of this research is the integration of three methodological components—virtual structural twins (Boje et al., 2020), *collapse coefficient* (**CC**) estimation, and supervised **ML** (Ruggieri et al., 2021)—into a coherent hybrid framework. The concept of a *virtual twin* (**VT**) is introduced as a simplified and representative digital model of a real building, built using geometric and mechanical data obtained from field observations and regulatory references. These models serve as the basis for limit analysis procedures.

The simplified analysis methodology is based on the static approach of limit analysis, implemented through the development of finite element procedures. These procedures establish the basis for self-tension spaces within the structures, where an ideal solution is sought using linear optimization algorithms. The computation process yields a **CC**, which quantifies the safety margin of a structure by evaluating the ratio between its structural capacity and the expected seismic demand. This coefficient is used to characterize vulnerability and prioritize real structures.

Another technical advance is in the coupling of this mechanical framework with **ML** techniques. Using data derived from the **VT** models and limit analysis, predictive algorithms

are trained to estimate seismic vulnerability based only on observable characteristics. This integration significantly increases scalability and speed and also decreases computation cost, maintaining a reliable level of accuracy in large-scale evaluations.

Another advantage in terms of risk mitigation against natural disasters lies in the ability to identify preexisting vulnerabilities with high susceptibility even to minor events. This facilitates the decision-making process and directs attention toward surveillance criteria and the prioritization of vulnerable structures that require immediate retrofitting.

1.6 State of the Art

The incremental methodology relies on plasticity theory, which becomes necessary when tracking the actual behavior of the structure. This involves solving equilibrium and compatibility equations incrementally over time steps while considering constraints. Plasticity theory, a subset of solid mechanics, deals with permanent strain accumulation during loading. In its traditional form, plasticity theory necessitates understanding non-holonomic constitutive laws incrementally, formulating solutions for balance equations over time steps, and establishing appropriate return algorithms.

Even though it demands stability properties in the Drucker (Ilyushin, 1948) sense for the constitutive law, limit analysis is fundamentally rooted in plasticity theory. However, it diverges from incremental equation integration. Instead, it defines the solution as an optimization-constrained program, yielding both a limit load level and a series of eigen-stresses that adhere to the constraints. The current dissertation employs a methodology to delineate the eigen-solutions set for a structural dilemma, constituting the domain of the optimal program for evaluating loading limits. Moreover, the material's compatibility domain aligns with the eigen-stress definition. The process centers on employing finite elements in a discontinuous format, generating a discrete operator linking the self-equilibrated stress set in the structure to discrete nodal displacement parameters. Within the finite element framework, it is pertinent to briefly discuss the method's evolution and various approaches over time.

The *finite element method* (**FEM**) represents a numerical analysis approach aimed at providing approximate solutions for a wide range of problems, spanning not only structural engineering but also physics, bioengineering, and astronomy. Initially devised for analyzing stress distributions in aeronautical structures, its application expanded to encompass the broader domain of continuum mechanics. Owing to its versatility and utility as an analytical tool, **FEM** has undergone significant development and finds extensive use across academic, industrial, and production settings. In numerous physical and engineering scenarios, obtaining approximate numerical solutions suffices, given the challenges associated with obtaining exact analytical solutions, which are often rare and difficult to derive. Consequently, numerical solutions have become standard references for experimental comparisons.

If a collapse mechanism is present wherein the stress state aligns with equilibrium conditions under the applied loads and remains consistent with the stress constitutive law, the structure

subjected to the applied load is deemed unsafe and prone to collapse. The two statements recalled above constitute the theorems of limit analysis in their more general formulation (Greenberg, 1949). A more particular formulation of Greenberg-Prager’s theorems that depends on the specific constitutive laws of the structural material is reported in the subsequent chapters, where a detailed description of the procedures is presented.

The subsequent widespread adoption of the method as a foundational tool for structural analysis was greatly facilitated by the progressive enhancement of computational power and the widespread availability of computers, as well as by advancements in both theoretical understanding and algorithmic techniques through ongoing research efforts.

The lower bound or static theorem of limit analysis.

When a stress state is identified that achieves equilibrium with the applied loads while remaining compatible with predetermined limits, the structure is deemed to be safe and resistant to collapse. Alternatively:

Upper bound or kinematic theorem of limit analysis.

If a collapse mechanism is present wherein the stress state aligns with equilibrium conditions under the applied loads and remains consistent with the stress constitutive law, the structure subjected to the applied load is deemed unsafe and prone to collapse.

1.7 Review of Similar Research

A number of studies have explored the mechanical modeling of **CC** structures for seismic vulnerability assessment (Borzi et al., 2008; Dimovska, 2023; Xofi et al., 2024). Researchers have adopted limit analysis frameworks, pushover-based evaluations, and incremental static methods across various contexts—from historical centers to modern urban zones. These include applications to cities such as Lisbon, Naples, and Catania, and also non-European cases like Istanbul, Mexico City, and Tehran. Each has contributed to refining modeling assumptions, typological classifications, and computational methods.

1.7.1 Macroseismic Models

Alongside mechanical methods, macroseismic models such as HAZUS (USA), EMS-98 (Europe), and DBELA have provided widely accepted frameworks for rapid seismic risk screening (FEMA, 2023; Grunthal, 1998). These models normally correlate expected damage with seismic intensity scales and structural typologies. Whereas they offer scalability and practicality, they often rely on empirical fragility curves and qualitative assessments, which may limit their reliability when applied to complex urban fabrics or nontypical RC configurations.

1.7.2 Statistical and Machine Learning Approaches

Recently, statistical and **ML** techniques have proceeded as strong tools for seismic vulnerability classification (Elyasi et al., 2024; Ferranti et al., 2024; Ruggieri et al., 2021). These data-driven

methods, including logistic regression, decision trees, and ensemble algorithms like Random Forest and XGBoost, have been used to predict damage levels or structural failure probabilities based on observed features. Although they require substantial training datasets, they provide the potential for rapid, scalable, and adaptable assessment, especially when integrated with mechanical outputs or remote sensing inputs. This dissertation builds on these advances to propose a hybrid approach that retains the rigor of mechanical modeling while benefiting from the efficiency of supervised learning.

1.8 Structure of the Thesis

This thesis includes ten chapters. Chapter 1 provides a detailed overview of the latest achievements in seismic vulnerability assessment methods and digital modeling strategies. Chapter 2 presents the theoretical background, including finite element analysis and the plasticity lower bound theorem. Chapter 3 describes the proposed two-phase hybrid method that integrates mechanical modeling and data-driven prediction. Chapter 4 presents the project goal and how to achieve it, which is vulnerability classification using finite element analysis and combining it with statistical information. Chapter 5 covers the providing the **VT** dataset and the related analyses, then Chapter 6 and Chapter 7 focus on the validation of the mechanical model and the extraction of the **CC**. Chapter 8 introduces the training dataset and the supervised learning techniques used to predict vulnerability. Chapter 9 discusses the applications, the interpretation of the results, and performance comparisons. Finally, Chapter 10 outlines the conclusions and possible future developments.

Chapter 2

Theoretical Background

2.1 Basis and Fundamentals of Finite Elements

The *finite element method* (**FEM**) is a powerful numerical technique in engineering and applied sciences to solve complex problems. Originally developed from the calculus of variations and energy principles, this method was formalized through weighted residue approaches, such as the Galerkin method (Zienkiewicz & Taylor, 2005). **FEM** allows the solving of complex problems in solid mechanics, structural engineering, fluid dynamics, and even heat transfer. Exact analytical solutions to these problems are impracticable due to irregular geometries, heterogeneous materials, and nonlinear behavior.

2.1.1 Origin and Principle of FEM

FEM operates with the principle of transforming a continuous domain into a discretized system of finite elements. Each element represents a simplified subdomain on which the solution is approximated using interpolation shape functions. The method begins by expressing the partial differential equations that govern in the weak variational form, which allows less rigorous continuity requirements and facilitates numerical integration.

In structural mechanics, the governing equilibrium equations can be derived from the principle of minimal potential energy or the principle of virtual work. These formulations lead to a system of algebraic equations:

$$\mathbf{f} = \mathbf{K}\mathbf{u} \quad (2.1.1)$$

where $\mathbf{K}$ is the global stiffness matrix assembled from elemental contributions, $\mathbf{u}$ is the displacement vector in the nodes, and $\mathbf{f}$ is the external force vector.

2.1.2 Discretization, Shape Functions, and Stiffness Matrices

The discretization process involves partitioning the domain into finite elements, each associated with nodes and degrees of freedom. Shape functions define how the field variable (e.g., displacement) varies within the element. Depending on the element type (triangular, quadrilateral,

tetrahedral, etc.), various polynomial functions are used. Each element contributes a local stiffness matrix, derived from the material’s constitutive behavior and geometric configuration. These local matrices are assembled into the global stiffness matrix using standard assembly procedures. The final system of equations, once boundary conditions are applied, can be solved using direct or iterative numerical solvers. References such as (Bathe, 2006) and (Hughes, 2003) provide rigorous treatments of stiffness formulation, convergence properties, and error estimation in **FEM**. Additional foundational texts, such as (Cook et al., 2007) and (Belytschko et al., 2014), also provide comprehensive treatments of **FEM** theory, especially in the context of solid and structural mechanics.

2.1.3 Application to Continuum Mechanics and *reinforced concrete* (RC) Structures

The **FEM** is particularly suited to the modeling of **RC** structures, as it can represent complex geometries and varying material properties. In RC applications, composite behavior is addressed either by smeared reinforcement models or embedded element approaches. Cracking, plasticity, and tension stiffening are also incorporated to capture the nonlinear behavior of concrete. In the current context, **FEM** is applied to model RC buildings subjected to gravitational and lateral (e.g., seismic) loads. The method allows for evaluating stress and strain distributions, identifying critical regions, and supporting further collapse and vulnerability analysis.

2.1.4 Relevance in Modeling Structural Collapse

While standard **FEM** implementations are geared toward elastic or mildly nonlinear analysis, assessing structural collapse requires specialized adaptations. Collapse phenomena involve large deformations, plastic redistribution of internal forces, and ultimate failure mechanisms. To capture this, **FEM** can be combined with plasticity theory and limit analysis frameworks. One approach is to embed yield criteria (such as von Mises or Mohr-Coulomb) within the finite element formulation and solve for limit states using incremental or optimization-based strategies. For instance, lower bound limit analysis can be formulated as a linear programming problem that seeks stress fields in equilibrium without violating yield conditions.

In recent developments, simplified grid-based **FEM** frameworks have been introduced to assess collapse capacity of large building stocks efficiently. These methods discretize the structure into rectangular elements, enforce static admissibility, and determine collapse multipliers through optimization. Such approaches are particularly valuable in urban-scale assessments where computational speed and robustness are essential.

In this research, **FEM** serves as the computational backbone for estimating collapse coefficients of RC buildings. The modeling strategy adopted is grounded in equilibrium-based finite element formulations, which are further integrated with observational data to support large-scale seismic vulnerability analysis.

2.2 Limit Analysis

2.2.1 Fundamentals of Plasticity Theory

Plasticity theory describes the behavior of materials that undergo irreversible deformations when subjected to loads exceeding their elastic limit. Unlike elasticity, which involves fully recoverable deformations, plasticity accounts for permanent strains. It is essential for analyzing structural performance under severe loading, such as during seismic events or progressive collapse scenarios.

The foundation of plasticity theory is the *yield surface*, an abstract boundary in stress space that separates elastic (fully reversible) behavior from plastic (permanent) deformation. A material behaves elastically as long as its stress remains within the yield surface. When the stress reaches this boundary, known as the yield stress, permanent or plastic deformation begins to occur. In structural engineering, common yield criteria include the von Mises criterion, which predicts yielding in ductile materials (e.g., steel), and the Mohr-Coulomb criterion, which applies to frictional materials such as concrete and soil (W. F. Chen & Han, 1988; Hill, 1998).

After yielding occurs, the *flow rule* defines the direction of plastic strain increments. If the plastic potential matches the yield function, as in metals, the flow rule is associated with it. For concrete or soil, non-associated flow rules are more suitable as they better capture dilatancy and softening (Chan et al., 2022).

Another key component is the *hardening law*, which governs the evolution of the yield surface as plastic deformation continues. In perfect plasticity, the yield surface remains constant, implying that further deformation occurs at constant stress. In strain-hardening or strain-softening models, the surface expands or contracts, indicating an increase or decrease, respectively, in the material's load-carrying capacity.

For structural applications, plasticity models must satisfy specific stability and consistency conditions—most notably those proposed by Drucker and Prager (1952)—to ensure that the material response remains physically admissible. These conditions are particularly important in numerical formulations, where convergence and uniqueness of the solution must be guaranteed.

Building on the foundations of plasticity theory, *limit analysis* seeks to determine the ultimate load-carrying capacity of a structure without performing incremental nonlinear analysis. By assuming rigid-plastic material behavior and idealizing the structure as perfectly plastic, limit analysis enables the identification of collapse mechanisms and critical load factors that characterize structural failure. While idealized, this approach offers powerful tools for both local and large-scale vulnerability assessment.

2.2.2 Limit Analysis Theorems

Limit analysis constitutes a specialized area within plasticity theory that determines the maximum load a structure can sustain prior to collapse. It is founded on two fundamental theorems — the Upper Bound Theorem and the Lower Bound Theorem — which together

provide a theoretical framework for assessing structural failure without simulating the complete load-deformation path.

2.2.2.1 Upper Bound Theorem

The Upper Bound Theorem states that any kinematically admissible failure mechanism provides a collapse load estimate that is equal to or greater than the actual collapse load. A kinematically admissible mechanism satisfies both compatibility and boundary conditions and maintains an internal plastic dissipation rate within the yield criterion (Salencon, 1983). By optimizing over all possible mechanisms, the minimum collapse load satisfying the kinematic admissibility condition can be determined.

2.2.2.2 Lower Bound Theorem

The Lower Bound Theorem provides a safe estimate of the collapse load when the stress field is statically admissible. The stress field must satisfy equilibrium and boundary conditions and remain within the yield criterion. This requires identifying a self-equilibrated stress distribution that does not exceed permissible stresses at any location in the structure (Maier, 1969). The lower bound approach ensures safety because any load derived from a valid stress field will not surpass the actual collapse load. However, identifying such stress fields is often challenging, particularly for complex geometries or structures composed of heterogeneous materials.

2.2.2.3 Conditions of Validity

Both theorems are based on the assumption of rigid-plastic material behavior, which neglects elastic deformations and assumes that structures deform through defined plastic mechanisms. The validity and applicability of these theorems depend on mathematical properties of the yield surface, such as convexity, and compliance with stability postulates as outlined by previous researchers (Drucker, 1959) and (Ilyushin, 1963). In practical applications, the actual collapse load is bounded by the values predicted by the two theorems; for computational modeling, the lower bound method is typically preferred to ensure structural safety, particularly when load conditions are uncertain or structural information is incomplete. Building on these principles, theorems form the conceptual basis for the numerical limit analysis strategies used in the present research, which estimate collapse capacity by applying optimization formulations to discretized representations of RC buildings.

2.2.3 Lower Bound Formulation and Optimization

The lower bound theorem of limit analysis provides a mathematically rigorous and computationally tractable framework for estimating collapse loads based on static criteria. This approach is essential for structural safety assessments because overestimating load capacity can compromise safety. In numerical analysis, the lower bound theorem is formulated as an

optimization problem to determine the maximum load factor that satisfies equilibrium and plastic admissibility constraints.

2.2.3.1 Static Admissibility and Stress Fields

A stress field $\boldsymbol{\sigma}$ is said to be statically admissible if:

1. It satisfies the equilibrium equations, including body forces and boundary stress;
2. It meets the prescribed boundary conditions;
3. It remains entirely within the elastic or yield surface, meaning that the yield criterion is not violated at any point in the structure.

In practical terms, for a given external load vector $\mathbf{f}$, the objective is to find a scalar load multiplier λ such that the scaled load $\lambda\mathbf{f}$ can be sustained by a stress field $\boldsymbol{\sigma}$ satisfying:

$$\text{div}(\boldsymbol{\sigma}) + \mathbf{b} = \mathbf{0}, \quad \boldsymbol{\sigma} \in \mathbf{Y} \quad (2.2.1)$$

where $\mathbf{Y}$ denotes the admissible yield domain (Maier, 1969; Salencon, 1983).

2.2.3.2 Optimization Framework

The problem can be formulated as a Linear Programming (LP) problem. In the discrete case (such as **FEM**), the unknowns are the nodal values or the stress components in the finite elements. The objective is to maximize the collapse multiplier λ , subject to:

- **Equilibrium constraints:** Ensuring that the internal forces balance the external loads;
- **Yield constraints:** Ensuring that the stress state in each element remains within the yield surface;
- **Additional optional constraints:** Such as symmetry, boundary behavior, or regularization for numerical stability.

Formally, the optimization problem can be expressed as:

$$\max_{\boldsymbol{\sigma}, \lambda} \lambda \quad \text{subject to:} \quad A\boldsymbol{\sigma} = \lambda\mathbf{f}, \quad \boldsymbol{\sigma} \in \mathbf{Y} \quad (2.2.2)$$

Here, A encodes the equilibrium equations and structural geometry, while $\mathbf{f}$ is the reference load vector.

This formulation identifies the collapse load without tracking the complete deformation history, resulting in computational efficiency for large-scale analyses. The scalar multiplier λ applied to the load serves as a clear indicator of structural safety. Values of λ less than one indicate premature failure, while values greater than one indicate reserve capacity.

2.2.3.3 Self-Equilibrated Stress Fields

In practical settings, particularly for statically indeterminate structures where internal forces cannot be determined solely from equilibrium equations, self-equilibrated stress states are advantageous. These stress distributions satisfy internal equilibrium independently of external loads and form the basis for constructing the admissible stress space in linear programming (LP) formulations (Chan et al., 2022).

Recent computational approaches, including those used in this research, discretize the admissible stress domain using grid-based **FEM** models. This discretization simplifies equilibrium constraints, which are mathematical conditions ensuring force balance within the model, and enables the optimization method to achieve strong convergence.

2.2.4 Application to Reinforced Concrete (RC) Structures and Collapse Assessment

RC structures display complex nonlinear responses under increasing loads, particularly during seismic events. Failure in these scenarios is typically governed by progressive plastic deformation and the development of collapse mechanisms. Traditional nonlinear dynamic analyses accurately capture this behavior but require detailed material modeling, incur significant computational costs, and necessitate extensive calibration. In contrast, limit analysis, which relies on rigid-plastic idealizations, provides a computationally efficient and theoretically robust method for estimating structural collapse capacity.

2.2.4.1 Justification for Using Limit Analysis in RC Buildings

RC buildings typically consist of beam-column systems that can be idealized as framed structures with defined load paths and failure modes. Many common collapse mechanisms—such as soft-story failure, plastic hinge formation, and column shear failure—share traits that can be approximated using plastic yield criteria and admissible kinematic or dynamic conditions (Salencon, 1983); (W. F. Chen & Han, 1988). By assuming rigid-plastic behavior, engineers can bypass detailed modeling of the elastic-to-plastic transition and focus directly on the structure’s ultimate capacity.

Limit analysis is particularly valuable in large-scale seismic vulnerability studies, especially when resources are limited and numerous buildings need to be assessed. In this context, ‘limit analysis’ refers to a method that assesses the maximum load a structure can withstand before collapsing. Because it provides conservative (lower-bound) or accurate (upper-bound) estimates of the collapse load, depending on the chosen formulation, this approach is well-suited for preliminary screening and decision-making under uncertainty.

2.2.4.2 Integration into Urban Vulnerability Frameworks

In this research, limit analysis is integrated into a wider framework for evaluating the collapse coefficient of **RC** buildings, establishing a connection between structural analysis and urban

vulnerability assessments. Each structure is represented using a grid-based finite element model, where plastic admissibility and equilibrium are enforced through lower-bound optimization (see Section 2.2.3). The outcome is a scalar *collapse coefficient* (**CC**) or λ , which is defined as the ratio of the estimated collapse load to the elastic threshold load:

$$\mathbf{CC} = \frac{S_C}{S_E} \quad (2.2.3)$$

where S_C is the structural capacity obtained from limit analysis and S_E is the reference elastic capacity. This coefficient serves as a quantitative vulnerability index, enabling the ranking and mapping of buildings in urban areas according to structural fragility.

2.2.4.3 Limitations and Considerations

Despite its advantages, the use of limit analysis in RC structures requires careful consideration of modeling assumptions:

- The rigid-plastic idealization may neglect important nonlinear behaviors such as cracking, confinement effects, or strain localization.
- Reinforcement details, which strongly influence ductility and failure modes, may not be explicitly included in simplified models.
- Shear failures and brittle collapse modes require special treatment or conservative assumptions in the yield criteria.

Nevertheless, when combined with observational data—such as geometric regularity, material quality, and construction period—limit analysis provides a reliable and scalable tool for risk assessment. This justifies its adoption as a core component of the methodology used in the present study.

2.3 Seismic Vulnerability and Background

2.3.1 Definition of Seismic Vulnerability

Seismic vulnerability is defined as the probability that a building, infrastructure, or system will sustain physical damage, functional loss, or collapse during an earthquake. This concept is fundamental to seismic risk analysis, in which risk is generally characterized by the combination of hazard, exposure, and vulnerability (Coburn & Spence, 2002).

$$\text{Seismic Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability} \quad (2.3.1)$$

Mathematically, seismic vulnerability is often expressed as a conditional probability:

$$P[D \geq d \mid IM = im] \quad (2.3.2)$$

where D is a damage measure (e.g., slight, moderate, collapse), d is the threshold damage state, and IM is an earthquake intensity measure (e.g., peak ground acceleration, spectral acceleration). This probabilistic formulation underpins *fragility curves*, which are widely used in both deterministic and probabilistic seismic risk assessments (Kappos et al., 2006; Rossetto & Elnashai, 2003).

The concept is not restricted to physical damage; it also encompasses a structure’s ability to maintain functionality and recoverability. In this broader context, vulnerability covers structural, architectural, and even sociol-economic dimensions (Milutinovic & Trendafiloski, 2003). Several factors influence a building’s seismic vulnerability, including:

- Structural system and materials,
- Geometry and number of floors,
- Age and compliance with building codes at the time of construction,
- Construction quality and maintenance,
- Plan or elevation irregularities.

Various approaches—ranging from empirical indices to analytical models—have emerged to quantify these influences. The following sections provide a detailed review of these approaches, setting the stage for the hybrid methodology adopted in this research.

2.3.2 Background and Historical Methods

Over the past five decades, seismic vulnerability assessment has undergone significant evolution, reflecting advancements in engineering knowledge and the increasing availability of data. Historically, methods for assessing building vulnerability can be broadly classified into three categories: empirical, analytical, and hybrid approaches.

2.3.2.1 Empirical Methods

Empirical approaches are based on observational data from past earthquakes and typically use post-event damage surveys to correlate building characteristics with observed performance. These methods generate vulnerability indices that assign qualitative or quantitative risk scores to specific structural typologies. Early examples include the Vulnerability Index Method developed in Italy (Benedetti & Petrini, 1984) and subsequently adapted in other European countries. The *rapid visual screening* (**RVS**) method, developed by the Federal Emergency Management Agency (FEMA) (FEMA, 2015), is also widely used and relies on visual inspections and the classification of building typologies.

Empirical methods offer simplicity and speed, making them effective for preliminary urban-scale risk mapping. However, they are limited by regional bias, restricted transferability, and challenges in representing complex structural interactions.

2.3.2.2 Analytical Methods

Analytical approaches utilize numerical modeling, structural analysis, and material behavior laws to simulate a building’s seismic response. Nonlinear static (pushover) and dynamic analyses are the main methods. These analyses provide detailed insights into structural demand and capacity. Fragility curves derived from these simulations express the probability of exceeding damage states as a function of seismic intensity measures (Rossetto & Elnashai, 2003). Compared to empirical or heuristic approaches, analytical methods provide more accurate, building-specific assessments, but require precise structural information, a significant modeling effort, and substantial computational resources. Thus, they have limited scalability to large urban areas.

2.3.2.3 Hybrid Methods

Hybrid approaches combine the strengths of both empirical and analytical techniques. For example, analytically derived fragility curves may be calibrated with observed damage data, highlighting how analytical methods can be cross-validated by empirical evidence. Conversely, empirical scoring systems can be refined using insights gained from simulations, demonstrating the enhancement of empirical methods through the application of analytical tools. Recent advancements include the use of logic tree frameworks to integrate multiple sources of uncertainty, providing a structure for assessing varied outcomes. Additionally, *machine learning* (ML) models trained on post-earthquake databases can predict building performance, further illustrating the synergy between data-driven and analytical approaches (Jimenez & Dela Cruz, 2024).

The hybrid approach is particularly relevant for this study. Integrating simplified structural modeling using limit analysis with observational features such as geometry, age, and construction quality enables scalable and interpretable vulnerability assessment at the urban level. This dual strategy constitutes the conceptual foundation of the methodological framework presented in the following chapters.

2.3.3 Parameters Influencing Vulnerability

Seismic vulnerability depends not only on seismic intensity but also on structural, architectural, and contextual factors. These factors influence how a building responds to earthquake loads and the potential extent of damage. Understanding them is essential for both analytical modeling and observational assessment.

2.3.3.1 Structural System and Materials

The type of structural system—moment-resisting frames (resisting lateral loads through rigid joints), shear walls (providing lateral strength through vertical walls), or dual systems (combining both)—is critical for a building’s lateral resistance and ductility. Materials such as **RC**, unreinforced masonry, or steel each have distinct failure modes and energy dissipation. For

example, non-ductile **RC** frames with poor detailing are much more vulnerable to seismic collapse (Hidayat et al., 2020).

2.3.3.2 Geometric Configuration

Building geometry—including plan and elevation regularity—affects how seismic forces spread. Irregularities such as setbacks, soft stories, or torsional eccentricities often cause stress concentrations and early failure (FEMA, 2015). Slenderness ratios, wall aspect ratios, and floor-to-height ratios also influence dynamic characteristics.

2.3.3.3 Number of Floors and Height

Low- to mid-rise buildings exhibit different behavior under seismic excitation compared to high-rise structures. Taller buildings are more susceptible to higher-mode effects (where upper floors move differently than lower ones during an earthquake), while shorter buildings may exhibit sudden plastic hinging (the rapid formation of zones where the structure yields). Studies show strong links between the number of stories and damage probability, especially for older **RC** frames (Milutinovic & Trendafiloski, 2003).

2.3.3.4 Age and Code Compliance

Buildings constructed before modern seismic codes often lack essential features, such as ductile detailing (the capacity for structural elements to undergo deformation without losing strength), confinement (additional reinforcement to prevent brittle failure), and lateral force-resisting systems (systems designed to withstand horizontal forces, such as those from earthquakes). As such, the construction period is a reliable proxy for code level and expected performance (Kappos et al., 2006).

2.3.3.5 Construction Quality and Maintenance

Even with sound design, poor construction practices and inadequate maintenance can severely compromise structural integrity. Concrete deterioration, reinforcement corrosion, and settlement-related damage are common factors that increase vulnerability (Aljaafreh et al., 2023).

2.3.3.6 Architectural Features

Heavy infill walls, overhangs, and open ground floors introduce discontinuities in stiffness and strength, which can compromise the overall structural integrity. These can compromise structural integrity. Often neglected in baseline models, such features significantly impact real-world performance and should be considered in empirical and hybrid assessments.

These parameters are the basis for many scoring and indexing systems and are also inputs for fragility modeling. In this dissertation’s methodology, parameters such as height, regularity, and construction period are extracted from observational data. They are then integrated into a vulnerability assessment framework supported by limit analysis.

2.3.4 Urban-Scale Assessment Techniques

Urban-scale seismic vulnerability assessment requires methods that are technically sound, scalable, and resource-efficient. While single-building assessments permit detailed modeling, large-area evaluations depend on simplified yet robust approaches that combine available data with structural logic and empirical observations.

2.3.4.1 Rapid Visual Screening (RVS)

RVS methods are widely used for preliminary vulnerability assessment in urban settings. Developed by FEMA (FEMA, 2015), **RVS** relies on systematic on-site inspections where surveyors assign vulnerability scores based on building characteristics and known weaknesses. These methods are valued for their speed and simplicity, allowing rapid screening of large building inventories. However, they are limited by subjectivity, dependence on visual indicators, and assumptions about typology behavior under seismic loading (Giovinazzi & Lagomarsino, 2004).

2.3.4.2 Index- and Scorecard-Based Approaches

Regional frameworks often use index-based systems that rate vulnerability using weighted criteria. The European RISK-UE project, for example, introduced a scorecard system that integrates structural, architectural, and environmental factors into a single index (Milutinovic & Trendafiloski, 2003). These indices can be mapped with *geographic information systems* (**GIS**) for comparative analysis. While effective for risk communication and prioritization, such approaches may oversimplify structural complexity or overlook material diversity and interaction effects.

2.3.4.3 Integration of Remote Sensing and GIS

Modern vulnerability assessments increasingly use remote sensing data, including satellite imagery, LiDAR scans, and street-view images, to automatically extract building features (Foulser-Piggott et al., 2016). Combined with **GIS**, these tools facilitate the large-scale mapping of vulnerability indicators, including building height, roof type, and plan irregularity. However, these techniques require validation, high-resolution data, and regionally calibrated algorithms.

2.3.4.4 Analytical Simplifications for Large-Scale Modeling

An emerging solution for urban-scale challenges is the use of simplified analytical models, such as grid-based finite element or capacity spectrum-based estimations, to simulate representative building typologies. Combining numerical modeling with typology classification enables more objective assessment of large inventories while maintaining reasonable accuracy (Lagomarsino et al., 2021).

This research adopts such a strategy by developing schematic **FEM** models for **RC** buildings and linking collapse indices to observable features from satellite maps and preliminary surveys. This hybrid approach supports both physical interpretability and spatial scalability.

2.3.5 Limitations of Traditional Methods

Traditional seismic vulnerability assessment methods—both empirical and analytical—have contributed to risk management and urban planning. However, they have limits that affect reliability, scalability, and applicability in different contexts.

2.3.5.1 Over-Simplification of Structural Behavior

Empirical and index-based approaches often use generalized typologies. These assumptions are based on the idea that all buildings in a class behave similarly. In reality, structures that appear similar can differ in material strength, detailing, foundation, and maintenance requirements. Standard scoring systems do not capture these differences, which can result in underestimating or overestimating vulnerability (Giovinazzi & Lagomarsino, 2004).

2.3.5.2 Lack of Structural Mechanics in Empirical Models

RVS and index methods often skip explicit mechanical modeling. As a result, they overlook key factors such as load paths, redundancy, failure modes, and energy dissipation. This limits the interpretation and transferability of results, especially for decisions involving retrofitting or emergency intervention (Rossetto & Elnashai, 2003).

2.3.5.3 High Resource Demand in Analytical Models

Numerical simulation methods, such as nonlinear static or dynamic analyses, give more accurate results. However, these methods are computationally expensive and require a substantial amount of data. Using them for large building inventories is often impractical, especially in places with limited resources or after disasters (Kappos et al., 2006). Additionally, obtaining accurate geometric and material details for thousands of buildings remains a significant challenge.

2.3.5.4 Limited Use of Observational and Spatial Data

Traditional methods rarely use spatially distributed data such as **GIS** layers, remote sensing, or crowd-sourced information. This limits adaptability to fast-changing urban areas or places where field data is hard to collect. New image analysis and artificial intelligence tools are still underused in these frameworks (Foulser-Piggott et al., 2016).

2.3.5.5 Insufficient Treatment of Uncertainty

Uncertainty in input data, modeling assumptions, and damage definitions is often overlooked or only implied, whereas empirical methods, in particular, rarely quantify confidence levels or

error bounds. This contrast reduces transparency and makes assessments harder to defend (Lagomarsino & Giovinazzi, 2006).

These limitations highlight the need for hybrid methods that strike a balance between physical accuracy and scalability. The framework in this dissertation addresses these issues by employing simple mechanical models and insights derived from large urban datasets. This approach makes vulnerability analysis for **RC** buildings in seismic regions more transparent, interpretable, and scalable.

2.3.6 Advances in Seismic Vulnerability Assessment Methods

This section and its subsections focus on recent developments, from 2020 to the present, in seismic vulnerability assessment methods for structures in Europe. Building on this period, recent research and accessible data sources have revealed several ideas that refine and extend the methodology developed in this study.

2.3.6.1 Advances in Rapid Visual Screening (RVS)

RVS methods have traditionally been essential, rapid, and low-cost tools for assessing large building inventories. Specifically, **RVS** involves visually inspecting buildings to quickly identify and prioritize structures with potential seismic hazards, often requiring minimal or no interior access. Since 2020, the integration of Artificial Intelligence (AI) and **ML** has become a significant trend in this field. By leveraging data-driven algorithms, these technologies increase the accuracy and efficiency of **RVS**.

ML models are now developed to perform binary classifications for different damage thresholds, such as Collapse Prevention (CP), Life Safety (LS), and Immediate Occupancy (IO). These thresholds describe increasing levels of building performance after an earthquake, with Immediate Occupancy representing minimal damage, Life Safety ensuring occupant protection, and Collapse Prevention denoting the minimum necessary to prevent building collapse. The models use features derived from Rapid Visual Screening (RVS), a method that involves quick, visual assessments of buildings to estimate their seismic vulnerability (Karampinis et al., 2024). This represents a shift from qualitative, expert-judgment-based screening to a more quantitative, data-driven process. ML algorithms trained on large datasets of earthquake damage and RVS features enable more consistent and more accurate assessments. This approach increases the reliability of preliminary screening and enables confident prioritization of buildings for detailed evaluation.

Techniques such as SHAP (SHapley Additive exPlanations), a method for assigning an importance value to each input feature in Explainable AI (XAI), now quantify the influence of each RVS (Rapid Visual Screening) parameter on classification outcomes (Karampinis et al., 2024). This transparency extends beyond the 'black box' paradigm, making AI outputs more interpretable for engineers. This quality is essential in engineering, where trust and interpretability are critical. Advanced **ML** approaches, such as collaborative filtering using

SVD (Singular Value Decomposition), and hybrid methods combining UMNN (Unconstrained Monotonic Neural Networks) with RFO (Red Fox Optimization), are being explored. These are used to provide customized retrofit recommendations and optimize RVS scoring (R Discovery, n.d.). Interest in AI within the earthquake engineering community is growing. Over 125 papers on AI applications were presented at the 18th World Conference on Earthquake Engineering (WCEE 2024). This marks a significant increase from previous conferences (NCSEA, n.d.).

RVS methodologies also adapt to regional characteristics and construction practices. For example, FEMA’s data collection form now includes local factors such as ground slope, foundation type, liquefaction potential, and specific structural configurations. These configurations include unreinforced masonry, confined masonry, stone masonry, and **RC** frames with unreinforced masonry infills (R Discovery, n.d.). This shows that effective rapid screening must consider the local building stock. Customizing RVS enhances the accuracy of preliminary assessments and provides a more accurate representation of actual seismic performance. This leads to more effective and targeted risk mitigation strategies.

Additionally, recent technological advances are supporting the practical deployment of RVS. For example, the development of Android-based frameworks for real-time assessment of existing buildings—such as hospitals—enables immediate collection of physical condition data and computation of seismic risk indices, further enhancing practical deployability (R Discovery, n.d.).

2.3.6.2 Utilizing Geospatial Technologies and Data Management

GIS play a pivotal role in linking index-based screening methods with spatial data. They support large-scale mapping of urban seismic vulnerability. This integration enables visual representation of vulnerability, analysis of various earthquake scenarios, and strong support for decision-making in disaster management and urban planning. **GIS** now serves as a central platform for merging diverse datasets and facilitating multi-stakeholder decision-making. It has evolved from being just a mapping tool. In Turkey, **GIS** is used extensively for managing building inventory data and assessment results. This enables the management of millions of buildings, real-time risk visualization, and the prioritization of timely interventions.

New **GIS**-based platforms are being developed to quantify and visualize various aspects of seismic risk. These include damage states, probability of significant damage, and direct economic losses (Filippou et al., 2024). These platforms serve as vital decision-making tools for many stakeholders, including policymakers, building owners, and insurance companies. **GIS** also facilitates the creation of geo-referenced building databases (GBD) by extracting, integrating, and processing data from multiple sources. These may include census, remote sensing, RVS, and expert judgment (Leggieri et al., 2022). This approach addresses the common challenge of data scarcity in large-scale applications. It enables rapid and comprehensive urban-scale seismic vulnerability assessments at low computational cost.

In addition to **GIS**, Building Information Modeling (BIM)—a digital representation of a building’s physical and functional features—is being explored for more accurate seismic loss

assessment, especially for instrumented buildings (Bahmanoo, 2021). BIM-based Application Programming Interfaces (APIs), which are software components allowing different programs to communicate, enhance seismic vulnerability evaluation by providing detailed information on building components and characteristics. This supports more accurate predictions of repair costs and downtime. BIM workflows integrate various stages of seismic analysis, including hazard analysis (assessing the likelihood of earthquake occurrence), structural analysis (evaluating a building's response to seismic forces), damage analysis (estimating physical impacts), and loss analysis (calculating costs and downtime). This holistic approach enables the prediction of seismic losses in terms of repair costs, downtime, and other key decision variables, offering a comprehensive view of potential post-earthquake consequences.

GIS provides city-scale overviews, while BIM offers component-level assessments of buildings. Together, they form a powerful multi-scale approach to seismic risk management. **GIS** provides a broad urban perspective for making macro-level decisions, while BIM offers detailed building-level information. This integration supports efficient large-scale planning and precise, performance-based interventions, thereby maximizing the effectiveness of risk reduction.

2.3.6.3 Advances in Fragility and Vulnerability Modeling

As part of the SERA project, a comprehensive database of capacity curves (graphs showing how a building responds to increasing loads), fragility functions (mathematical models estimating the probability of damage at different seismic intensities), damage-loss models (methods to estimate physical damage and economic losses), and vulnerability functions (relationships indicating the likelihood of various damage states for specific building types) for various classes of European buildings—classified according to GEM Building Taxonomy v3.1 (an international standard for categorizing building types)—has been compiled and developed (Crowley et al., 2020). These models are publicly available on the EFEHR platform and contribute to the European Seismic Risk Model 2020 (ESRM 2020). This coordinated effort to develop and standardize vulnerability functions and fragility curves for European building typologies directly addresses the need for consistent and comparable risk assessments across national borders. Without such standardization, comparing seismic risk between countries would be difficult due to varying vulnerability assumptions. This would hinder the evaluation of transnational risks and the development of more effective EU-wide disaster management strategies.

Countries such as Portugal are utilizing these advances to develop new probabilistic seismic risk models, which incorporate updated vulnerability functions for numerous specific building classes (e.g., 116 classes) and include data from the latest national census (Lopes et al., 2024).

Fragility curves remain vital tools, as they illustrate the probability of a building reaching or exceeding specific damage states at varying levels of seismic intensity. Creating them requires detailed building inventory data, often combining RVS, remote sensing, national housing databases, and expert judgment (Roy et al., 2023). Furthermore, buildings are classified by typology, construction material, age (linked to seismic design codes), and other critical attributes that influence seismic performance.

There is a clear shift toward linking seismic vulnerability to more advanced ground motion intensity measures, especially response spectra. Previously, assessments mostly relied on macroseismic intensity or peak ground acceleration (PGA) (Calvi et al., 2006). For instance, macroseismic intensity, such as EMS-98, provides a qualitative measure of effects, while PGA gives a single peak value. In contrast, response spectra provide a more complete picture of the frequency content of ground motion, which in turn relates directly to how structures with different natural periods respond. As a result, this technical evolution makes vulnerability assessments more accurate and performance-based, effectively bridging the gap between broad risk estimates and detailed structural engineering analyses.

Recent research also explores multi-objective optimization methods such as Particle Swarm Optimization (PSO). These are used to optimize the design of load-bearing components under seismic loading, aiming to improve both performance and efficiency. Meanwhile, new Ground Motion Prediction Models (GMPMs) are being developed using richer, updated databases of strong motion records, including recent major earthquakes in Turkey. As a result, these models provide more consistent estimates and reduced residuals for ground motion parameters, such as PGA, PGV, and PSA. This, in turn, improves the accuracy of seismic demand inputs for vulnerability assessments.

2.3.7 Country-Specific Advances and Key Initiatives in Europe

2.3.7.1 Italy

Italy, with its rich architectural heritage and long history of destructive earthquakes, has consistently been at the forefront of seismic vulnerability assessment research and implementation in Europe. Since 2020, the focus has been on vulnerability indices and their application at the urban scale. Italian approaches often rely on the development of “vulnerability indices” derived from visual inspections and key structural attributes, typically linked to the European Macroseismic Scale (EMS-98). Urban-scale seismic risk assessment methodologies have been applied in cities such as Castelfranco Emilia, ranging from single-building surveys to comprehensive analyses of the urban fabric (Baldassarre et al., 2024). These initiatives underscore Italy’s commitment to evolving and applying methods that mitigate seismic risk across diverse urban environments. Research efforts have been directed toward particularly vulnerable building typologies, notably **RC** school buildings. Continuous emphasis is also placed on the vulnerability assessment and risk analysis of existing masonry buildings—especially in historic city centers—recognizing their unique structural features and cultural significance. This dual focus on heritage buildings and critical infrastructure, such as schools, reflects a culturally sensitive, comprehensive approach to seismic risk reduction. Ongoing projects aim to define damage scenarios for cities such as Florence, where a high percentage of the building stock predates seismic code enforcement (Paoletti et al., 2024). Italian seismic codes align with modern international standards, emphasizing life safety and damage limitation (Civil Protection Department, n.d.). Italy also plays an active role in EU-funded projects, such as ADRISEISMIC (INTERREG V-B Adriatic-Ionian

ADRION, launched in 2020), which focuses on sharing effective approaches and developing tailored roadmaps for reducing seismic vulnerability in the Adriatic–Ionian region (Marzani et al., 2025).

2.3.7.2 Greece

Greece, located in a highly seismically active region, continues to prioritize the assessment of its dominant building typology—**RC** structures—with special attention to vulnerabilities such as “short columns”, a phenomenon where columns are unintentionally stiffened by non-structural infill walls and are more prone to damage. Recent methodological developments (2020–present) include the evolution and application of Rapid Visual Screening (RVS) forms and scoring systems, which are tools for quickly assessing and ranking the seismic risk of buildings, often led by Greek universities and research institutes. A notable initiative involves the formulation of Artificial Neural Network (ANN) models, specifically Feedforward Neural Networks (FNN), which are **ML** techniques used to predict how structures will respond—measuring acceleration, velocity, and displacement spectra—for single-degree-of-freedom systems (idealized models that consider one direction of movement) using an extensive strong-motion database from Greek earthquakes recorded since 2000 (Pitilakis et al., 2024).

Innovative mobile applications, such as RiskSchools, have been developed for large-scale seismic resilience assessments of critical infrastructure, including school buildings, by integrating physical vulnerability and risk classification into a user-friendly platform. Greece is also an active partner in ADRISEISMIC, collaborating with other Adriatic–Ionian countries to identify and share best practices for seismic vulnerability reduction through policy and regulatory frameworks (Marzani et al., 2025).

2.3.7.3 Turkey

Following a series of devastating earthquakes, Turkey has made significant investments in seismic vulnerability assessment and risk reduction, becoming a leader in large-scale rapid assessment programs, especially in densely populated urban centers such as Istanbul. Since 2020, the development and large-scale implementation of rapid visual assessment and scoring systems have continued, typically managed by municipal authorities and disaster management agencies. These methods focus on key vulnerability factors, such as the year of construction (linked to seismic codes), the number of floors, the presence of irregularities, and the general maintenance condition.

Building on this rapid assessment infrastructure, a hallmark of Turkey’s approach is its extensive use of **GIS** to manage vast building inventory data and vulnerability assessment results, enabling efficient data visualization, analysis, and prioritization of intervention. Furthermore, significant progress has been made in developing new Ground Motion Prediction Models (GMPMs) for shallow crustal earthquakes, calibrated with an extensive and continuously updated strong-motion database (1976–2023) from Turkey and surrounding regions, including major recent seismic events.

2.3.7.4 Romania

Romania, particularly its capital, Bucharest, faces significant seismic risk from the intermediate-depth Vrancea source, posing a serious threat to its large stock of pre-code high-rise concrete buildings built during the communist era. A notable development within the period examined is the launch of the EVR (Electronic Visual Building Assessment) platform in 2022 (Ministry of Development, Public Works and Administration, 2022). This platform, derived from Romania’s national seismic risk reduction strategy, facilitates rapid visual screening, a national building inventory, and risk ranking for prioritizing seismic retrofitting investments. However, the platform explicitly clarifies that EVR assessments are intended solely for prioritization of retrofitting needs and are not comprehensive seismic risk classifications as defined by the P100-3 design code. These assessments are preliminary and do not reflect detailed structural analyses or legal risk designations. Challenges include outdated regulations, lack of updated building data, and public misinterpretations of EVR results, which can create a false sense of security (Ioan Cuza, 2021; Pavel & Nica, 2024). Studies are also actively evaluating the performance of the 2020 European Seismic Hazard Model (ESHM20) against instrumental records and macroseismic observations in Romanian cities, noting that results should be interpreted cautiously due to limited spatial and temporal coverage (Manea et al., 2025).

2.3.7.5 Portugal and Spain

Both Portugal and Spain face moderate to high seismic risk in specific regions, particularly along southern coasts. Building on these risks, Portugal has made significant advances, including the development of new probabilistic seismic risk models that incorporate updated national datasets, such as a 2021 census-based residential building exposure model, a recent model for commercial and industrial buildings, and updated vulnerability functions for 116 building classes (Lopes et al., 2024). These models enable the precise identification of building typologies that disproportionately contribute to total seismic risk, allowing for more targeted retrofitting strategies. Similarly, Spain has conducted probabilistic seismic hazard analysis (PSHA) for critical infrastructure, notably 48 dams in Andalusia, using recently defined seismic source zones and providing results for PGA and PSA (Zacchei & Molina, 2022). Urban-scale seismic vulnerability assessments have focused on social housing built between 1965 and 1975, often with minimal seismic considerations, aiming to create open **GIS** databases to identify structural deficiencies (Mehralian et al., 2024). Additionally, historical earthquake loss scenarios (e.g., Torre Vieja 1829, Arenas del Rey 1884) have been modeled using methods such as the USGS PAGER to enhance public awareness and inform policymakers (Elez et al., 2025). While there is no explicit national RVS program in Spain, academic research on applying **ML** to RVS classification is active (Karampinis et al., 2024).

2.4 Definition of Collapse Load and Collapse Coefficient

2.4.1 Collapse Load

The collapse load represents the maximum load a structure can sustain before global failure or collapse occurs. Within the framework of *Limit Analysis*, this load is obtained without simulating the entire nonlinear load–deformation path. Instead, assuming rigid–plastic material behavior and satisfying equilibrium and yield conditions, the ultimate capacity can be directly determined through optimization techniques (Salencon, 1983). This approach contrasts with conventional nonlinear analyses that rely on incremental methods to track the progressive development of damage. In limit analysis, the collapse load is defined as the point at which either an admissible static stress field or an admissible kinematic mechanism satisfies the failure conditions.

2.4.2 Elastic Threshold vs. Ultimate Capacity

To quantify structural performance, it is essential to distinguish between the elastic threshold capacity and the ultimate (collapse) capacity. The elastic threshold, denoted S_E , refers to the load at which the structure departs from linear elastic behavior—typically associated with first yield. The ultimate capacity, S_C , corresponds to the collapse load identified through limit analysis. While S_E is useful for serviceability assessments, it often underestimates the reserve strength that many structures possess due to ductility and their ability to redistribute forces. Assessing S_C allows engineers to understand the true safety margin and to prioritize retrofitting or emergency interventions based on the actual structural behavior.

2.4.3 Definition and Role of the Collapse Coefficient

To standardize assessment and enable comparison between buildings, the **CC** is defined as:

$$\mathbf{CC} = \frac{S_C}{S_E} \quad (2.4.1)$$

This scalar coefficient provides a direct and interpretable index of seismic performance. A value of $\mathbf{CC} \approx 1$ indicates limited ductility and minimal reserve strength, while $\mathbf{CC} > 1$ suggests that the structure has additional capacity beyond its elastic limit. Conversely, low values of $\mathbf{CC} < 1$ may indicate structural deficiencies or modeling inconsistencies.

2.4.4 Interpretation and Implications in Structural Assessment

The collapse coefficient acts as a quantitative link between analytical modeling and vulnerability classification. In this study, it is used to rank **RC** buildings according to their relative safety margin under seismic loading. By mapping **CC** values across urban areas, high-risk zones can be identified and risk reduction efforts prioritized. Furthermore, because **CC** is derived from

simplified yet mechanically consistent models, it retains physical meaning while being scalable to large building inventories. When combined with observational indices (such as regularity, age, and construction quality), this coefficient becomes a key input in hybrid frameworks for seismic vulnerability assessment.

2.5 Integrated Numerical–Observational Approach for Assessing Reinforced Concrete Buildings

2.5.1 Rationale for the Hybrid Approach

Assessing the seismic vulnerability of large numbers of **RC** buildings in urban areas presents a dual challenge: on one hand, detailed structural analysis requires precise geometric and mechanical data along with complex numerical modeling; on the other, applying such methods to hundreds or thousands of buildings is time-consuming, resource-intensive, and often impractical under real-world constraints. This tension between analytical accuracy and operational scalability motivated the development of the hybrid approach proposed in the present research.

Conventional methods can be broadly divided into two categories. First, purely numerical methods—such as nonlinear static or dynamic analyses—provide high accuracy but are not feasible at large scale due to modeling complexity, data requirements, and computational load. Second, empirical or index-based approaches (e.g., Rapid Visual Screening or scoring systems) offer speed and ease of implementation but lack a strong physical basis and are often limited in interpretability, particularly for non-standard building types or retrofitted structures. In this context, the proposed method aims to bridge the gap between these two extremes. By integrating observational data—extracted from maps, satellite imagery, or building records—with simplified mechanical modeling based on limit analysis, the framework achieves a balance between detail and scalability. The collapse capacity of each structure is computed using a finite element-based model (VFEMGridwork), yielding the **CC**. This coefficient is then adjusted using additional parameters that capture age, geometric regularity, and material quality—derived from observational surveys—to produce a refined safety index termed *SafeScore*.

This integration enables a more nuanced classification of buildings: rather than relying solely on typological categories, each building is evaluated based on its unique numerical response and observed characteristics. As a result, the hybrid method combines physical validity with regional scalability, making it suitable for urban seismic microzonation. Moreover, the approach is designed to produce outputs directly usable by urban planners: color-coded vulnerability maps, classification tables, and scalable “abacus” charts linking structural patterns to relative risk. These outputs—grounded in numerical logic and informed by real-world data—form a core contribution of this research to seismic risk mitigation.

2.5.2 Sources of Observational Data

In this study, observational data play a key role in complementing numerical analysis by documenting real-world structural conditions, geometries, and material qualities. To obtain these data, accessible tools such as Google Maps, Google Earth, and *quantum geographic information system* (**QGIS**) were used in combination with engineering judgment and building mapping logic.

Google Maps provides an accessible platform for visual inspection of buildings and their surroundings. With minimal training, a technician familiar with basic geolocation tools and building systems can extract a wide range of relevant structural features. For instance, visual cues from street-view images and satellite photos can reveal building typology, maintenance status, number of stories, and even apparent material quality. The presence and arrangement of windows and openings can offer insight into the number of structural bays, while the spacing and number of columns can often be inferred by closely analyzing the rhythm and regularity of the facade. Key structural vulnerabilities—such as short columns or soft stories—can also be identified from visual inspection, especially when combined with a basic understanding of structural behavior. The 3D building mode in Google Earth adds another interpretive layer, enabling assessment of vertical irregularities and overall volumetric regularity, both of which are significant indicators of seismic performance.

Despite their utility, these tools have specific limitations. Google’s mapping services are designed primarily for general public use—navigation, business location, and route planning—rather than structural assessment. Similarly, high-resolution, classified geospatial datasets often require purchase agreements or licensing. Furthermore, systematic extraction of data at large scale demands customized workflows and trained operators capable of accurately interpreting the data.

QGIS—an open-source geographic information system—offers greater analytical capacity, including georeferencing, layer management, and integration with cadastral or engineering datasets. However, effective use of **QGIS** in this context depends on access to reliable geospatial datasets and skilled users who can configure and manipulate the software for structural mapping purposes. Thus, while these tools provide scalable access to spatially distributed building data, their integration into a technical framework for vulnerability assessment requires both methodological customization and a certain level of human expertise. In this study, such tools served as the primary gateway for extracting observational parameters, which were later integrated with numerical model outputs to compute the *SafeScore* for each building.

2.5.3 Parameters Extracted from Visual Observation

The identification and classification of buildings in this study relied on direct visual analysis of publicly available mapping tools—primarily Google Maps and Google Earth—supplemented by engineering insight and contextual experience. A structured approach was adopted to extract key structural parameters influencing seismic vulnerability, ensuring both feasibility

and interpretability.

2.5.3.1 Structural Material Type

The primary classification criterion was the structural material of each building. While remote visual identification has inherent limitations, prior experience in design and construction supervision in urban environments—combined with familiarity with architectural patterns in regions such as Tehran and southern Italy—enabled relatively reliable distinctions. For example, masonry buildings typically exhibit characteristic features such as arched windows, thick walls, and traditional facade patterns, which contrast with the clearer vertical alignment and uniform bay spacing of concrete or steel structures. The relative dimensions of ground-floor columns and wall thickness further assist in differentiating **RC** from steel frame systems, as RC columns are generally wider and more robust in the lower stories.

2.5.3.2 Plan Configuration and Regularity

Plan geometry was another key parameter. Buildings with highly irregular plans—resulting from owner-specific space maximization or architectural preferences involving projections, recesses, or internal courtyards—were excluded from the analysis. Such shapes introduce significant complexity in *virtual twin* (**VT**) modeling, particularly in finite element meshing and in predicting collapse mechanisms. The remaining buildings were classified based on plan regularity, with preference given to approximately rectangular or square footprints that facilitate structural modeling. This classification ensures the consistent application of grid-based **FEM** and limit analysis.

2.5.3.3 Vertical Regularity

Residential buildings typically maintain consistent floor area and column layout across vertical levels, ensuring geometric regularity and stiffness. Consequently, vertical irregularity is generally not a concern in these cases. However, in urban non-residential buildings—particularly those with commercial ground floors or architectural terraces—vertical irregularities are more common. In this study, a coefficient-based approximation was used to estimate vertical irregularity, with recognition that more precise quantification is warranted in future work.

2.5.3.4 Age and Maintenance Condition

Visual inspection of facades, roof types, and signs of material degradation enabled estimation of construction age and overall maintenance status for each building. Older structures often show evidence of weathering, outdated construction details, or lack of seismic retrofitting—all of which are associated with higher seismic vulnerability. These observations were converted into quantitative modifiers within the *SafeScore* framework.

These observational parameters were systematically recorded and used to complement the numerical results obtained from collapse analysis. By integrating visual data with mechanical

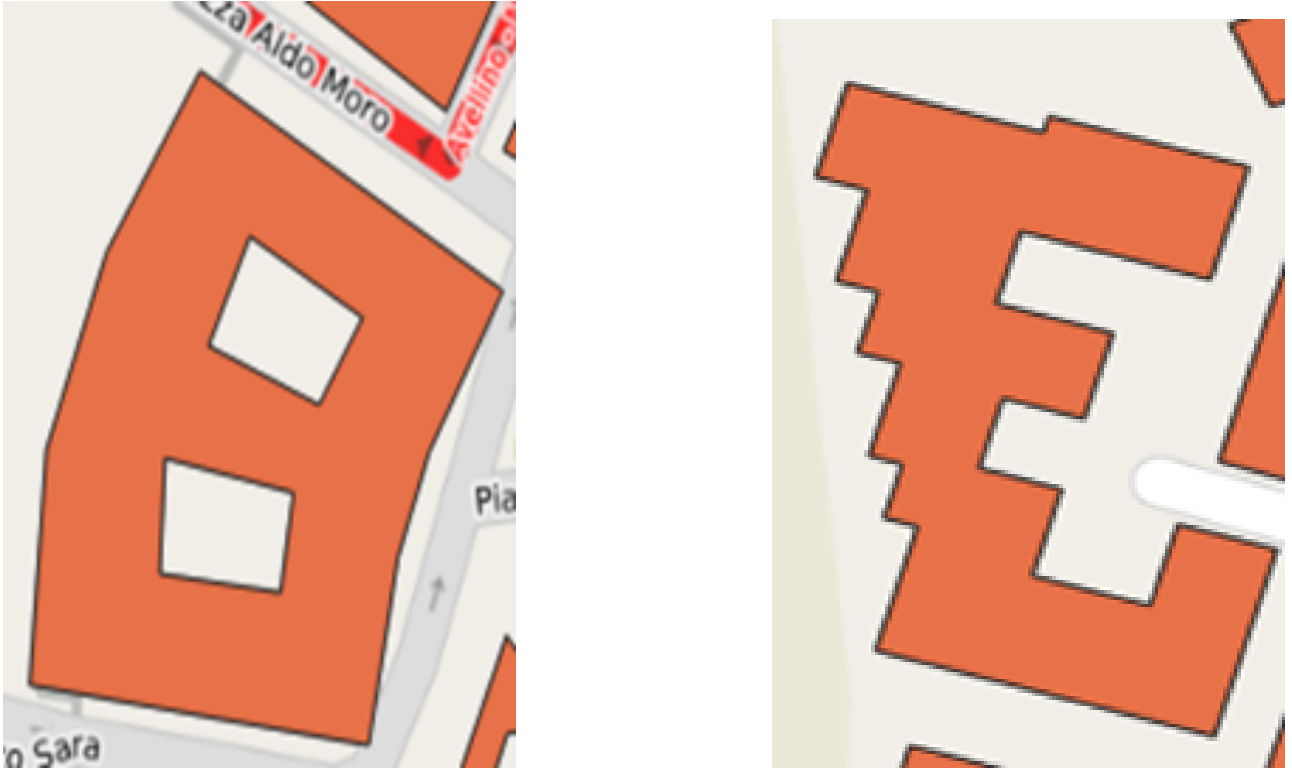


Figure 2.1: Example of complex plans excluded from the dataset. Large internal openings and irregular layouts, often designed for increased daylight or architectural space, introduce significant modeling complexity and were therefore omitted.

modeling, the assessment achieves a more accurate and realistic characterization of the seismic vulnerability of each structure.

2.5.4 Numerical Modeling and Integration

The numerical backbone of this research is built upon a simplified yet mechanically consistent finite element framework grounded in limit analysis. The modeling approach adopted in this work is a direct result of the methodological tradition developed by Professor Minutolo’s research group, which emphasizes physical interpretability, computational efficiency, and scalability for city-scale structural assessment.

The modeling process begins with the generation of simplified three-dimensional (3D) frame structures representing key types of existing **RC** buildings in urban contexts. These models are developed in a preprocessing environment—ANSYS in this case—and are prepared for limit analysis using a customized **VFEMGridwork** routine. The latter performs lower-bound collapse analysis with displacement-based finite elements and linear programming optimization, as introduced earlier and described in detail in the doctoral work of Renato Zona (Zona, 2021).

2.5.4.1 Simplifications and Assumptions in the Model

To enable systematic analysis and rapid production of structural models, several assumptions were made, each reflecting a balance between practical necessity and engineering judgment:

- **Uniform floor height:** All buildings were modeled with a constant floor height of 3 m. While this is a general standard in residential construction, future studies may evaluate the sensitivity of collapse coefficients to variations in floor height.
- **Regular bay distribution:** The total building length in both East–West and North–South directions was divided into equal bays. This ensures plan regularity and simplifies **FEM** meshing. The number of bays in each direction was determined based on the observed geometry of actual buildings.
- **Fixed section dimensions:** All vertical members (columns) were assigned identical rectangular cross-sections. Similarly, beams were grouped into two distinct types based on orientation: one section type for East–West beams and another for North–South beams. These assumptions reduce the number of variables and allow for more consistent interpretation of output parameters across building floors.
- **Material properties:** A single set of material properties was adopted for all RC components, consistent with typical urban RC construction. The effect of variable material strength (e.g., concrete compressive strength) was incorporated into the *SafeScore* through the parameter ζ , derived from observational estimates.

This modeling protocol enables the automated generation of a large number of virtual buildings—referred to as **VTs**—that serve as idealized numerical representations of real structures. Each **VT** is defined by a unique combination of geometric and structural features, encoded in the file name and traceable through the analysis pipeline.

2.5.4.2 Limit Analysis via VFEM and Collapse Load Estimation

Numerical analysis was carried out using the **VFEMGridwork** approach, which is based on displacement-based finite elements and limit analysis principles. As explained in (Zona, 2021), this method employs a lower-bound plasticity formulation in which a basis of self-equilibrated stresses is constructed from geometric compatibility constraints. Internal forces are represented as linear combinations of nodal pseudo-displacement parameters, and the collapse load factor is obtained via a linear programming optimization that maximises the applied load factor while satisfying yield criteria.

This formulation—rooted in Melan’s lower-bound theorem—provides an efficient alternative to incremental nonlinear analysis. It directly yields the collapse load (S_C) without the need to simulate the full deformation history. The elastic threshold load (S_E) is obtained by analyzing the same frame under elastic behavior, assuming nominal material strengths. The **CC**, as defined earlier, is here used as a scalar performance metric derived from the ratio of collapse capacity to elastic capacity:

$$\mathbf{CC} = \frac{S_C}{S_E} \quad (2.5.1)$$

To clarify the computational accuracy of the collapse coefficient, it is essential to understand how the elastic and collapse loads— S_E and S_C respectively—are extracted. While the **CC**

formula provides a convenient scalar representation, the actual estimation of S_C involves a complete optimization procedure rooted in lower-bound plasticity theory. Following the approach developed in the VFEM framework by Zona, the internal stress field is formulated via displacement-based finite element discretization, in which the stress components are linearly related to the nodal pseudo-displacement parameters δ . The collapse factor is then obtained as the solution to a constrained optimization problem:

$$\sup_{\delta} \{k \mid (k\sigma^* + V\delta) \in D_e\} = s_\alpha \quad (2.5.2)$$

where:

- σ^* is the reference elastic stress state,
- $V\delta$ represents the combination of special stresses generated by displacement modes,
- D_e is the elastic domain bounded by yield criteria (e.g., biaxial moment–axial force interactions),
- k is the load factor to be maximized.

The elastic domain D_e is often linearized for computational tractability using polyhedral approximations such as flat-face enclosures of the 3D yield surface. The optimization ensures that no stress component exceeds the section capacity in either axial or bending conditions (e.g., N_z , M_y , M_z). This guarantees that $S_C = k \cdot S_E$ is not only a nominal collapse factor but the outcome of an admissible and bounded plastic stress state.

In this formulation, the $\sup_{\delta}$ operator denotes the supremum (least upper bound) of the load factor k over all admissible pseudo-displacement parameter sets δ . This represents the highest value of k for which the combined stress field $k\sigma^* + V\delta$ remains entirely within the elastic domain D_e . The result of this optimization problem, denoted as s_α , is referred to as the *collapse coefficient*: a scalar that quantifies the maximum ratio of the reference load the structure can sustain without violating any yield criterion. In practice, this coefficient defines the theoretical ultimate load capacity of the structure under the assumptions of rigid–plastic behavior and fully known geometry and boundary conditions.

This formulation enables robust comparisons between building types and supports the construction of performance-based vulnerability charts. Rather than relying on empirical fragility or heuristic scores, it provides a theoretical basis for defining safety classes. Thus, the *CC* acts not only as a convenient output but as a synthetic result of a fully physically and mathematically consistent collapse assessment framework.

2.5.5 Synthesis: Hybrid Workflow

2.5.5.1 Rationale for a Hybrid Method

Seismic vulnerability assessment of urban **RC** buildings requires a balance between accuracy and feasibility. Purely numerical approaches—although physically rigorous—are often impractical for

large stocks due to their demand for precise input data and high computational costs. Conversely, observational or index-based methods—such as visual surveys or scoring systems—are scalable but lack structural depth and mechanical grounding.

This duality motivates the development of a hybrid method that strategically combines field-observable features with simplified structural simulations. By doing so, the method leverages the strengths of both data domains: the realism and accessibility of observational data, and the analytical accuracy of numerical modeling. The hybrid approach is particularly suited to urban environments where direct access to buildings is limited and timely vulnerability mapping is essential for seismic risk mitigation and emergency response planning.

2.5.5.2 Complementary Nature of Observational and Numerical Data

The observational dataset consists of features retrievable from satellite imagery, street-view photos, maps, and, where available, cadastral or engineering records. These features include structural typology, footprint dimensions, estimated number of floors, facade quality, material clues, plan and elevation regularity, and maintenance condition. Such data are accessible, cost-effective, and interpretable with limited field effort, especially when assessed by engineers familiar with the local construction culture.

On the other hand, numerical models are generated as **VTs** from a structured library of parametrically defined RC frame configurations. These models are designed to capture the fundamental load-resisting behavior under lateral seismic actions. Finite element models are analyzed using a lower-bound plasticity formulation (**VFEMGridwork**) that outputs the **CC**—a metric quantifying a building’s capacity to withstand lateral load before failure. The key innovation lies in how these two sources of information interact: the numerically obtained **CC** is adjusted by observational indices to yield a composite safety index. Observational data provide context-specific modifiers—such as aging effects, irregularity factors, or material quality estimates—that realistically tune the mechanical response.

2.5.5.3 Implementation Workflow

The complete workflow, illustrated in Figure 2.2, consists of four main steps:

1. **Data collection:** Extract geometric and contextual parameters from Google Maps, Earth, and **GIS** layers. Key fields include number of floors, estimated year of construction, plan regularity, and maintenance indicators.
2. **VT assignment:** Match each real building with a corresponding predefined numerical model, ensuring typological consistency while applying assumptions for standardization (e.g., fixed floor height, uniform bay lengths).
3. **Limit analysis via VFEM:** Use the **VFEMGridwork** engine to compute elastic and collapse loads (S_E , S_C) and evaluate the **CC** as defined earlier in Section 2.4.

4. **SafeScore computation:** Integrate the **CC** with observational modifiers ($\alpha, \beta, \gamma, \delta, \varepsilon$) as follows:

$$SafeScore = CC \times \alpha \cdot \beta \cdot \gamma \cdot \delta \cdot \varepsilon \quad (2.5.3)$$

where each factor represents a modifier based on a specific observational feature such as construction age, plan irregularity, or facade quality.

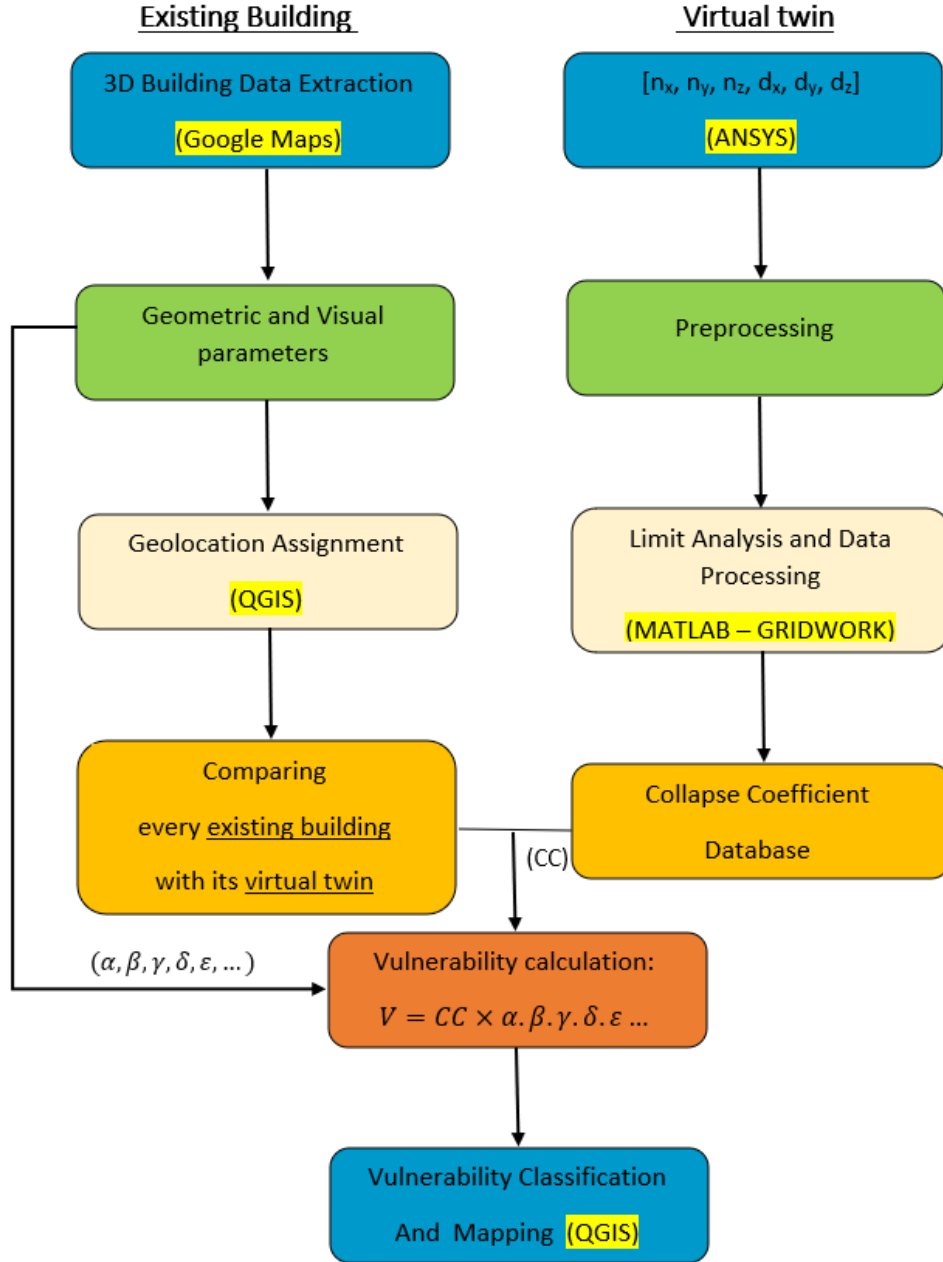


Figure 2.2: Process diagram of the hybrid workflow.

2.5.5.4 Advantages and Anticipated Applications

The hybrid workflow facilitates the production of color-coded vulnerability maps, decision-support tools (e.g., performance-based charts), and building safety rankings that can guide

authorities in prioritizing inspections, retrofitting programs, and emergency interventions.

Furthermore, this approach promotes transparency: both the analytical reasoning (from limit analysis) and field evidence (from visual indicators) are explicitly embedded in the decision-making process. This integration enables better communication with stakeholders and improves public trust in seismic risk assessments.

In summary, the hybrid method bridges the gap between mechanical simulation and real-world observability by combining numerical accuracy and observational accessibility in a cohesive, scalable workflow. It enables rapid yet evidence-based seismic vulnerability assessments suited to complex urban scenarios, aligning scientific rigor with operational feasibility.

Chapter 3

Methodology

3.1 Collecting Urban Building Data Using Available Tools

For the seismic vulnerability assessment of urban buildings, access to geometric, structural, and qualitative data for each structure is essential. In cases where no integrated and reliable database exists, public and free resources such as Google Maps and open-source software like *quantum geographic information system* (**QGIS**) are valuable tools for extracting fundamental information (Google, n.d.; QGIS Development Team, n.d.).

In this study, an urban area in Italy—previously affected by seismic events—was selected as the case study. Similar to many other urban zones, this area contains a mix of unreinforced masonry buildings in its historic center and *reinforced concrete* (**RC**) residential structures in both older and more recent developments.

By leveraging Google Maps and Google Street View, parameters such as plan dimensions, number of floors, facade conditions, and construction patterns for each building were visually inspected and measured. Where direct street-level visibility was limited due to building density or privacy constraints, the 3D view feature of Google Earth was used to observe the buildings from alternative perspectives.

Subsequently, using **QGIS** software, the precise geographic coordinates of each building were extracted, and the raw data were stored in a dedicated geographic information layer. These datasets served as the foundation for generating schematic structural models in the following stages of the project.

3.2 Definition of Structural Types, Selection of Suitable Data, and Geometric Preprocessing

After collecting the observable building data, the next step was to refine and categorize the structures based on their structural material. Initially, all buildings were classified into four main groups: **RC**, masonry, steel, and other types. Preliminary investigations showed that

approximately 70% of the buildings in the study area were of RC construction. Since the focus of this research is on RC structures, more comprehensive data for this group were collected and processed.

Furthermore, over 80% of the building stock consisted of residential structures with relatively regular engineered plans. This facilitated the selection of suitable samples for numerical modeling and increased the accuracy of the subsequent analyses. The data were structured for modeling purposes, and features such as plan length and width, aspect ratio, story height, total number of stories, and the ground floor position were standardized and sorted in ascending order.

To reduce uncertainty and prevent potential errors in the modeling stage, buildings were assigned dedicated type codes based on their geometric characteristics. This classification was performed according to two main criteria:

1. **Geometric characteristics:** including plan dimensions (length and width), story height, total building height, and the number of columns in each direction. This served as the basis for assigning each building a *virtual twin* (**VT**) model to be used in the subsequent analysis stages.
2. **Visible and qualitative characteristics:** including facade condition, structural system, maintenance quality, approximate building age, and an evaluation of plan or elevation irregularity. These factors were later incorporated as corrective coefficients in the seismic vulnerability assessment phase (discussed in later chapters).

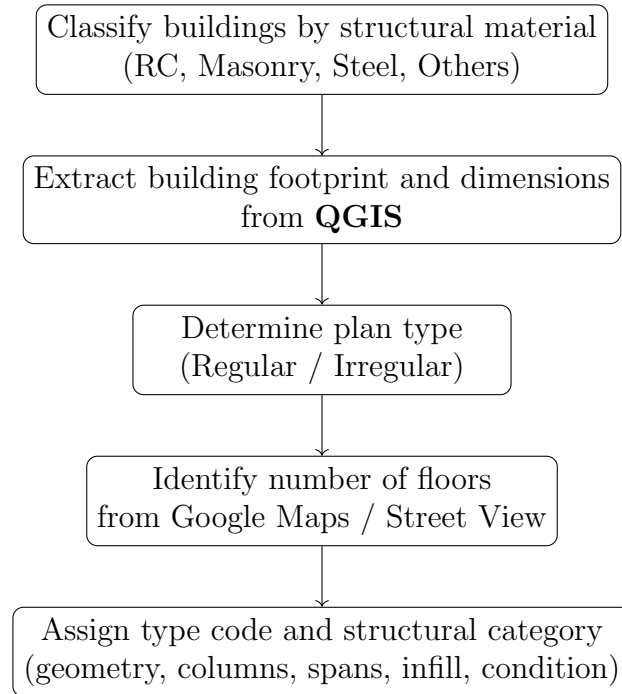


Figure 3.1: Flowchart of the data preprocessing and structural classification process.

3.3 Modeling in ANSYS and MATLAB–GRIDWORK

After classifying the buildings and extracting their geometric data, the next step was to convert this information into numerical models for structural analysis. The modeling process in this research followed a step-by-step approach, combining two main software tools: ANSYS as the geometric preprocessing and meshing platform, and MATLAB with the custom-developed GRIDWORK framework for limit analysis.

3.3.1 Geometric Preprocessing in ANSYS

In the first stage, three-dimensional structural frame models were created in ANSYS based on the specifications extracted from Google Maps and related tools. The focus at this stage was on generating simple, regular three-dimensional frames that accurately represented the plan geometry and total height of each building. The main parameters used in defining these models included:

- Span lengths in both X and Y directions;
- Floor height of 3 m for **RC** residential buildings;
- Total number of floors;
- Cross-sectional dimensions of elements (representative of actual column and beam sizes in each direction);
- Simplified boundary conditions (fixed supports at the column bases);
- Material properties including elastic modulus, Poisson’s ratio, compressive strength, and other relevant characteristics.

The aim of this step was to produce a mesh and geometric dataset that could be directly transferred for use in MATLAB, rather than performing any structural analysis within ANSYS itself. No static or dynamic analyses were carried out in ANSYS. Instead, a scripted procedure was employed to automatically feed the building parameters into ANSYS, which then generated the required model geometry. For each three-dimensional frame, six separate text files were exported, containing numerical data on geometry, material properties, boundary conditions, load definitions, and other relevant parameters.

3.3.2 Model Transfer to MATLAB and the GRIDWORK Framework

Once the models were prepared in ANSYS, they were exported as structured numerical files and imported into MATLAB. At this stage, the GRIDWORK framework—developed by the research team—was used to perform the numerical analysis. This framework is based on the Lower Bound Theorem of Melan and is designed to evaluate the ultimate load-carrying capacity of a structure as an optimization problem.

In this approach, the structure is modeled as a three-dimensional frame composed of compression and bending members. The allowable stresses of each member are defined according to the material strength, and the objective is to find the optimal internal force distribution that satisfies overall equilibrium without exceeding these stress limits.

The lower bound limit analysis provides a direct estimation of the ultimate collapse load without requiring assumptions about incremental behavior or the complete stress-strain curve. Therefore, this method is particularly suitable for fast and robust collapse capacity assessment of structures, especially when dealing with large-scale building datasets.

3.4 Calculation of the Collapse Coefficient for Each Virtual Twin

In this project, for each sample building, a structural model was developed with geometric and mechanical properties matching those of the real structure. This model, referred to as a **VT**, represents a concept that has been refined in previous research conducted by our group, aiming to simplify and systematize the numerical analysis of buildings at an urban scale.

The foundation of this approach was established by Prof. Minutolo and the research team, inspired by the Lower Bound Theorem in structural mechanics. Combining engineering insight with numerical computation, they designed a set of simplified three-dimensional frames, each representing a specific building typology. This collection consists of 6,300 structural models, systematically generated based on the combination of three main parameters:

- **Number of floors:** from 1 to 7 (7 levels)
- **Bay length in each direction:** 3 to 8 m ($6 \times 6 = 36$ combinations)
- **Number of bays in each direction:** from 3 to 7 ($5 \times 5 = 25$ combinations)

The combination of these three parameters resulted in exactly 6,300 distinct geometric typologies, which form the basis of the **VT** dataset for seismic assessment. From this set, a selection of models was made to ensure optimal variety in geometric configurations. For each selected model, numerical analysis was performed using the GRIDWORK framework to calculate the *collapse coefficient* (**CC**). The calculation procedure for this coefficient was described in Chapter 4.

It is worth noting that the **CC** is a dimensionless and scalable index that expresses the overall load-carrying capacity of a structure, accounting for the nonlinear material behavior and stress distribution in its members. The **CC** values for different buildings indicate variations in their actual capacity to withstand seismic loads and serve as the primary basis for defining seismic vulnerability in later stages of the analysis.

Given the diversity of building geometries in urban areas, two main strategies could be adopted to extend these models.

1. **Increasing the number of VT typologies** so that every possible geometric configuration has a representative model. In this case, buildings are matched to their corresponding **VT**, and the precomputed analysis results are assigned to them. This method is simpler and faster, but may have reduced accuracy for atypical structures.
2. **Developing the MATLAB analysis program** to accommodate a broader range of real geometries, enabling independent analysis for each building. This method is more accurate and stable but comes with higher computational and time costs.

This stage of the research marked the starting point for integrating *machine learning* (**ML**) methods. By learning from the mechanical analysis results, **ML** models can predict the response of new building configurations with high speed and acceptable accuracy. This aspect is discussed in detail in Chapter 8.

3.5 Definition of the Safety Index by Combining Qualitative Factors

While the **CC** provides valuable information about the ultimate capacity of a structure, a more realistic assessment of seismic vulnerability also requires the inclusion of qualitative factors. These factors include building age, maintenance condition, and the degree of regularity in plan and elevation.

For this purpose, a final safety index, referred to as the *SafeScore* (SS), was defined as a combination of the **CC** and four corrective coefficients:

$$SS = \mathbf{CC} \times \alpha \times \beta \times \gamma \times \delta \quad (3.5.1)$$

where:

- α : Coefficient for maintenance condition
- β : Coefficient for building age and initial seismic design level
- γ : Coefficient for plan irregularity
- δ : Coefficient for elevation irregularity

Table 3.1 presents the values assigned to each coefficient based on field observations and qualitative classification.

Table 3.1: Qualitative coefficients assigned to observed parameters.

Parameter	Category	Value	Category	Value
Maintenance condition (α)	Poor	0.80	Fair	0.90
	Good	1.00		
Building age / seismic design (β)	Old / low seismic design	0.70	Conventional design	1.00
	Modern	1.10		
Plan irregularity (γ)	≥ 2 irregularities	0.65	1 irregularity	0.80
	None	1.00		
Elevation irregularity (δ)	≥ 2 irregularities	0.65	1 irregularity	0.80
	None	1.00		

In this formula, the **CC** obtained from the numerical structural analysis serves as the baseline. Multiplying it by the qualitative coefficients yields the SS, which reflects the actual safety condition of a building under seismic loading.

The SS index is used as the final basis for classifying buildings in terms of safety and prioritizing intervention measures. In the following section, it will be shown how this index—after minor modification—can also serve as the vulnerability index. Furthermore, SS will be employed in subsequent chapters for generating seismic risk maps and training **ML** models.

3.6 Final Definition of Safety Classification and Vulnerability Levels

After calculating the **CC** and adjusting it with the qualitative coefficients to obtain the final SafeScore (SS), the last step in the methodology is to classify buildings into seismic vulnerability levels. First, all $SS > 1.0$ values were capped at 1.0, then the resulting scores were normalized to $[0, 1]$ and categorized.

3.6.1 SafeScore Classification

The normalized SS index was divided into four levels:

Table 3.2: SafeScore (SS) classification levels.

Level Code	Lower Bound	SS Range	Upper Bound	Safety Interpretation
D1	0.80	$< SS \leq$	1.00	High safety – no vulnerability
D2	0.50	$< SS \leq$	0.80	Medium safety – minor retrofitting required
D3	0.20	$< SS \leq$	0.50	Vulnerable – major retrofitting required
D4	0.00	$\leq SS \leq$	0.20	Very vulnerable – near/complete collapse

3.6.2 Final Vulnerability Index

Given that safety and vulnerability are complementary in $[0, 1]$, the final vulnerability index is:

$$V = 1.00 - SS \quad (3.6.1)$$

Table 3.3: Final seismic vulnerability levels (V) with color coding.

V Level	V Range	Class Code	Color Code	Safety Label
V1	$0.00 \leq V < 0.20$	C1	Green	Safe
V2	$0.20 \leq V < 0.50$	C2	Yellow	Needs further inspection
V3	$0.50 \leq V < 0.80$	C3	Red	Requires intervention
V4	$0.80 \leq V \leq 1.00$	C4	Black	Highly vulnerable

3.6.3 Basis and Use

Thresholds were set by preliminary statistical analysis, comparison with past earthquake evidence, and alignment with EMS-98 damage grades (D0–D5). The color-coded four-level scheme will be used for micro-zonation maps in the next chapter; in Chapter 8, the mechanically derived **CC** will serve as the target variable for **ML** models. This scheme supports prioritization, budgeting for retrofitting, and safety labeling of buildings.

Chapter 4

Vulnerability Classification and Mapping

The seismic vulnerability assessment of urban buildings is a critical necessity in disaster management and in planning for the seismic retrofitting of structures. In this chapter, inspired by recent research developments, a method is introduced that enables the classification and mapping of the seismic vulnerability of *reinforced concrete* (**RC**) buildings in urban environments with both accuracy and simplicity. Rather than relying solely on detailed structural analyses or costly on-site inspections, this method employs *finite element limit analysis* (**FELA**) alongside basic geometric and material properties of structures — data that can be obtained from remote sensing or existing databases. The aim is to identify high seismic-risk zones within a city with acceptable accuracy and in the shortest possible time. The subsequent sections of this chapter outline the workflow of this approach, from numerical modeling and classification of buildings to the visualization of results in a *geographic information systems* (**GIS**) environment and the statistical analysis of the outputs.

4.1 Aim: Microzoning of the Built Environment

The primary objective of seismic microzoning in this study is to provide a simple, rapid, and feasible framework for identifying high-risk areas in the urban fabric, based on the structural characteristics of existing buildings. In contrast to conventional methods that primarily focus on geotechnical data or ground response, the emphasis here is on assessing the seismic vulnerability of existing buildings. At the initial stages of this method, there is no requirement for detailed geotechnical information or ground response analysis, since data regarding seismic intensity and expected ground acceleration can be extracted from extensive previous studies conducted in various urban areas in Europe, and are readily available for many regions. The micro-zoning procedure that couples mechanics-derived collapse metrics with urban mapping follows the framework of Zona et al. (2025).

Accordingly, this approach, by relying on simplified numerical analyses and existing structural data, enables a relative identification of the safety condition of buildings. Subsequently, by

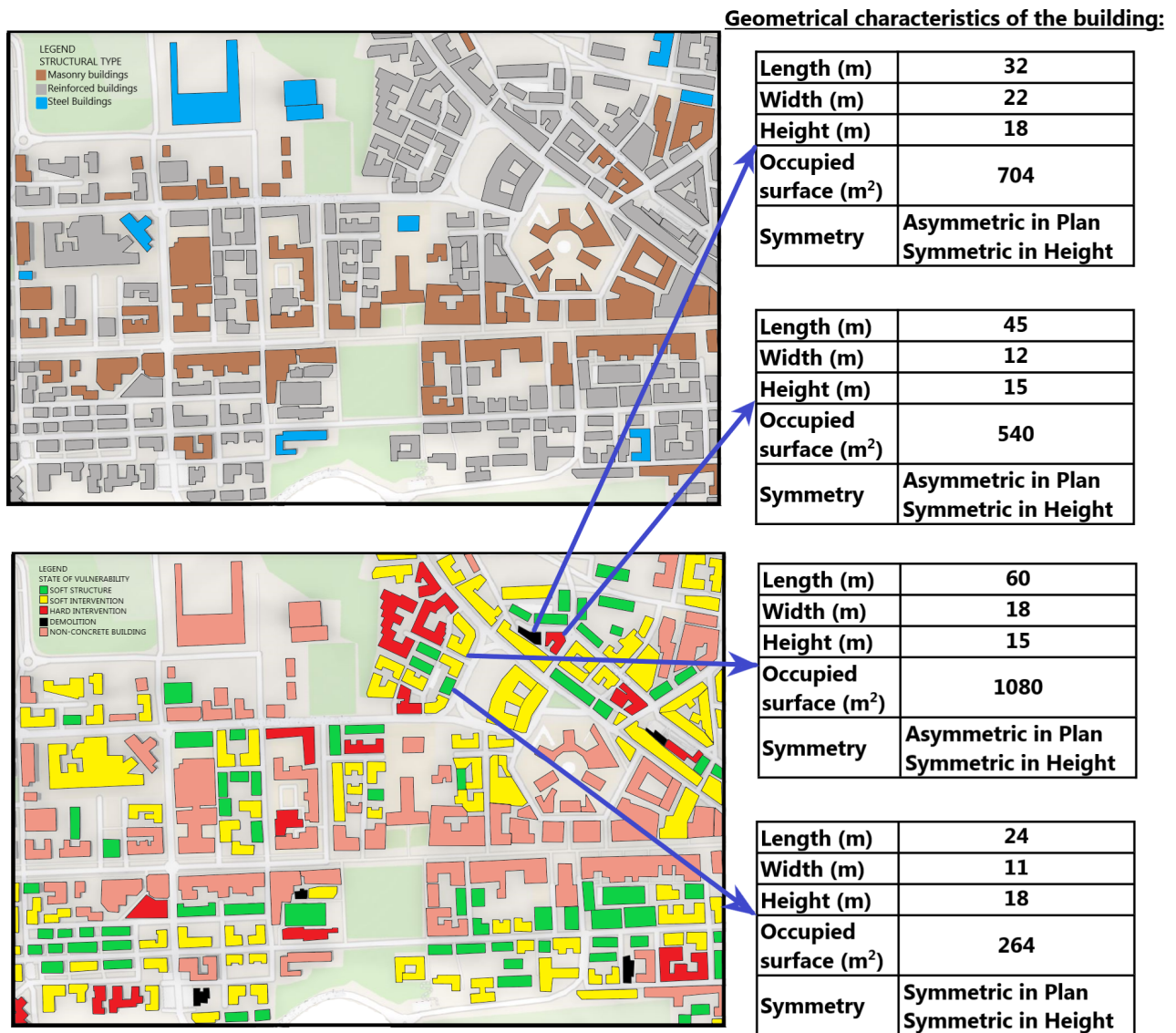


Figure 4.1: Seismic micro-zoning map of the study area. *Reproduced from Zona et al. (2025).*

classifying buildings into different vulnerability levels, maps can be generated that highlight critical zones in terms of seismic risk, supporting urban managers in prioritizing interventions and allocating resources. A key feature of this method is its independence from site-specific geotechnical conditions, meaning it can be applied to any region by updating general seismic parameters.

4.1.1 Review of Similar Methods and Frameworks

In recent years, several studies have aimed to simplify the process of seismic vulnerability assessment of buildings, particularly at the urban scale. Some of these works have sought to replace complex structural analyses with simplified analytical approaches, statistical models, or empirical indices that can be applied for rapid evaluation during crisis situations or in the planning phase.

For instance, in studies focusing on unreinforced masonry (URM) or **RC** buildings, methods such as collapse mechanism-based (CMB) analysis, lower-bound limit analysis, or capacity estimation using limited structural data have been employed. Other research efforts have proposed integrated frameworks that combine structural data with **GIS** or demographic datasets. Although these studies have not directly implemented **FELA**, they share significant conceptual similarities with the present approach, including: emphasis on simplification, use of readily available data, and orientation towards rapid decision-making at the urban scale.

Moreover, existing review studies in this field have demonstrated that simplified analytical methods, when carefully designed and properly validated, can serve as a reliable alternative to more complex methods at a large scale. Table 4.1 summarizes some of these studies and their relationship to the present approach.

Table 4.1: Comparison between the present method and similar methods/frameworks

Reference	Scale	Method	Common Points with Present Study
Shabani et al., 2021	URM, urban scale	SAMs; capacity spectrum analysis	Simplification; use of limited data.
Malena et al., 2022	Historical structures	Modal analysis; stepwise FEA	Two-stage workflow; limit analysis.
Zhang et al., 2024	Urban	Open data; FEA; GIS	Urban-scale integration; GIS-based pipeline.
Ferretti et al., 2024	RC/masonry buildings	Simplified modeling; PGA-based classification	Closest in spirit to FELA .

4.2 Method: Finite Element Limit Analysis (FELA)

This method is employed here as an efficient tool to estimate the ultimate load-carrying capacity of structures and to determine the *collapse coefficient* (**CC**). The formulation is grounded in the Lower Bound Theorem and static admissibility, and is used to provide a rapid proxy of seismic vulnerability for **RC** buildings at the urban scale. Two complementary implementations are considered in this project:

- **Z-FEM**: a discontinuous finite element formulation that relates displacement jumps to self-equilibrated internal stresses through a stress operator $\mathbf{Z}$.
- **SAM**: a semi-analytical approach based on Melan’s assumptions, together with a kinematic (yield-line) hypothesis.

4.2.1 Lower-Bound Formulation

The lower-bound problem seeks the largest load factor that does not violate yield constraints anywhere in the domain. Following (Zona, 2021), the optimization problem can be stated as:

$$s_\alpha = \sup_k \text{ subject to } f(k\boldsymbol{\sigma}^* + \mathbf{Z}\boldsymbol{\delta}) \leq \mathbf{0}, \quad \alpha \in \{\text{sd}, \text{c}\}, \quad (4.2.1)$$

where:

- s_α is the admissible load factor for state α ; sd denotes shakedown and c denotes collapse,
- $\boldsymbol{\sigma}^*$ is the elastic stress field under the reference (base) loading,
- $\mathbf{Z}\boldsymbol{\delta}$ represents a self-equilibrated stress field induced by displacement discontinuities in the discontinuous FE model,
- $f(\cdot)$ is the yield function (linear or convex), defining the admissible stress domain,
- k is the load scaling factor, maximized without violating the yield constraints.

4.2.2 Polyhedral Yield Domain

For computational tractability, the yield surface is approximated by a convex polyhedral set. In stress space, admissibility can be written as the set of linear inequalities:

$$f(\boldsymbol{\sigma}) \leq \mathbf{0} \implies \mathbf{A}\boldsymbol{\sigma} \leq \mathbf{b}, \quad (4.2.2)$$

with $\boldsymbol{\sigma}$ the stress vector, $\mathbf{A}$ the matrix of facet normals, and $\mathbf{b}$ the vector of admissible bounds. This polyhedral approximation reduces the lower-bound analysis to a (large but sparse) linear program, enabling the evaluation of many typified structural models with adequate accuracy and low computational cost—an essential feature for urban-scale applications.

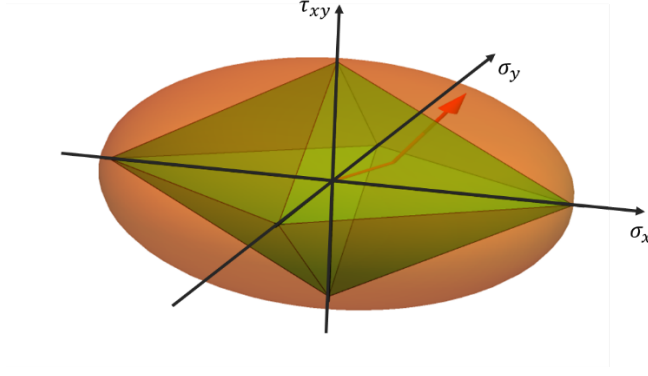


Figure 4.2: Schematic polyhedral approximation of the yield surface in stress space.

4.2.3 Determination of the Collapse Coefficient and its Relation to Vulnerability

In this study, the principal output of the limit analysis is the **CC**, defined conceptually as the ratio between the critical load that triggers collapse and the corresponding elastic reference load. For clarity:

- **SC**: the critical load estimated by the lower-bound analysis;
- **SE**: the elastic reference load obtained from a simplified elastic analysis.

The value of **CC** expresses the relative seismic resistance of a building: values closer to one indicate proximity to the limit state and, therefore, higher vulnerability; larger values indicate a greater safety margin. This indicator serves as the basis for the building classification carried out in the next step of the analysis.

4.2.4 Z-FEM: Key Advantages

Z-FEM provides a discontinuous finite element framework wherein the stress operator **Z** maps displacement jumps onto self-equilibrated internal stresses. Its main advantages in the present context are:

- rapid numerical modeling of typified RC frames,
- reliance on low-cost inputs (geometry and basic material properties),
- scalability to the urban level and straightforward integration with statistical datasets,
- compatibility with downstream machine-learning models for surrogate prediction.

In summary, the FELA-based workflow (via Z-FEM and SAM) yields a numerical indicator of ultimate resistance that will be used in the next subsection to construct a four-level vulnerability classification and the corresponding urban maps.

4.3 Four-Level Vulnerability Classification

After computing the **CC** via **FELA**, each building is assigned to one of four seismic vulnerability levels based on its estimated structural safety. The classification is driven by a safety indicator, here termed the *SafeScore* (SS), which is directly derived from the collapse coefficient.

In this approach, the **CC** is successively modified by qualitative factors that affect safety, such as building age and design level, geometric irregularity, maintenance quality, total height, and plan configuration. These modifiers are defined with a clear directionality: if a factor improves safety, its multiplier is set greater than one; if it degrades safety, it is set lower than one.

The final SafeScore is computed as:

$$\text{SafeScore} = \mathbf{CC} \times \alpha_{\text{age-design}} \times \alpha_{\text{height irregularity}} \times \alpha_{\text{plan irregularity}} \times \alpha_{\text{maintenance}} . \quad (4.3.1)$$

Here, **CC** is the collapse coefficient obtained from FELA and α_i denote the qualitative multipliers associated with each contributing attribute.

SafeScore values exceeding 1 are truncated to 1 since “more than 100% safety” is not meaningful. The resulting values are normalized to the $[0, 1]$ range. The vulnerability index is then defined as the complement of the safety index, $V = 1 - \text{SafeScore}$. Thus, for each building we obtain a dimensionless value between 0 and 1, comparable across the sample. This value is mapped to one of the four vulnerability classes. The classification is purely numeric (i.e., no clustering or *machine learning* (**ML**)) and is based on performance thresholds defined by the research team, calibrated to reflect urban-scale retrofit standards and crisis-management prioritization. Table 4.2 summarizes the four-level classification.

Table 4.2: Summary of the four-level seismic vulnerability classification

Description	Range of V	Color	Vulnerability Level
Adequate resistant capacity; no immediate action required	$0.0 \leq V < 0.2$	Green	Level 1 — Safe
Relative safety; requires case-by-case review	$0.2 \leq V < 0.5$	Yellow	Level 2 — Relatively Safe
Structural deficiencies under seismic loading	$0.5 \leq V < 0.8$	Red	Level 3 — Moderately Vulnerable
Immediate detailed assessment and retrofitting needed	$0.8 \leq V < 1.0$	Black	Level 4 — Highly Vulnerable

4.3.1 Practical Example of the Classification

To illustrate the practical workflow, a sample of real data used in this study is presented. Information for approximately 30 existing buildings in the study area was compiled using satellite imagery, street-view resources, and spatial analysis tools such as Google Maps and *quantum geographic information system* (**QGIS**). Next, by interpreting the apparent geometry

and identifying the lateral load-resisting system of each building, a simplified three-dimensional model was created for each structure. These models were then evaluated in MATLAB using FELA, and the **CC** was computed for every case.

Finally, combining this indicator with qualitative observations (e.g., approximate age, the number of irregularities in height and in plan), the SafeScore and the corresponding vulnerability level were obtained for each building. The results are displayed in the next section as urban maps and analytic layouts within **QGIS**.

Table 4.3 shows an excerpt of the dataset.

Table 4.3: Sample of the real dataset used in this study.

building id	length m	width m	height m	floors	plan. Reg.	elev. Reg.	maintenance	age+design	lon.	lat.	frame name	CC	SS	SSn	V
AVL-0005	40	15	15	5	0.8	1	1	0.9	14.78387631	40.91585463	Telaio_5.5.3.8.5	1.3295	0.95724	0.943987425	0.056012575
AVL-0010	32.2	11	15	5	1	1	0.9	0.9	14.78450455	40.9161285	Telaio_7.5.2.4.6.5.5	1.0834	0.877554	0.839604401	0.160395599
AVL-0011	35	14	21	7	1	0.8	0.9	0.9	14.78442005	40.91592885	Telaio_2.7.7.7.5	1.0001	0.6480648	0.538989783	0.461010217
AVL-0012	33	15	15	5	0.8	1	0.8	0.9	14.78433374	40.91572815	Telaio_4.5.8.4.4	1.0001	0.5760576	0.444665444	0.555334556
AVL-0017	50	16	15	5	0.8	0.8	1	0.9	14.79231556	40.91814597	Telaio_10.5.4.5.4	1.0811	0.6227136	0.505781504	0.494218496
AVL-0026a	48	21	12	4	0.8	1	1	0.9	14.7932262	40.91582064	Telaio_8.4.3.6.7	1.2467	0.897624	0.865894682	0.134105318
AVL-0026b	40	9	6	2	1	1	0.9	0.9	14.79309532	40.91601935	Telaio_8.2.2.5.4.5	1.1741	0.951021	0.935840975	0.064159025
AVL-0027	38.5	25	9	3	0.8	0.8	1	1.1	14.7884033	40.91443346	Telaio_7.3.5.5.5.5	1.2144	0.8549376	0.809978517	0.190021483
AVL-0029	50	30	3	1	0.8	1	0.9	0.9	14.79005635	40.91576165	Telaio_10.1.6.5.5	1.0001	0.6480648	0.538989783	0.461010217
AVL-0033	36	20	6	2	1	1	1	0.9	14.77846558	40.91824839	Telaio_9.2.4.4.5	1.191	1.0719	1	0
AVL-0038	55	28	6	2	0.8	1	1	0.9	14.77831241	40.91492519	Telaio_11.2.7.5.4	1.1738	0.845136	0.797139114	0.202860886
AVL-0039	54	22	6	2	1	0.8	0.9	0.9	14.7806891	40.91452424	Telaio_9.2.4.6.5.5	1.203	0.779544	0.711218234	0.288781766
AVL-0042	42.5	22	6	2	0.8	0.8	0.9	0.9	14.7844676	40.91487175	Telaio_5.2.4.8.5.5.5	1.017	0.5272128	0.380682211	0.619317789
AVL-0049	24	18	15	5	1	1	1	0.9	14.7910197	40.91367205	Telaio_3.5.4.6.6	1.0001	0.90009	0.869124967	0.130875033
AVL-0050	25	13.5	15	5	0.8	1	0.9	0.9	14.79157409	40.9137387	Telaio_5.5.3.5.4.5	1.0728	0.6951744	0.600700026	0.399299974
AVL-0051	32	16	12	4	0.8	1	1	0.9	14.79172472	40.91417999	Telaio_8.4.4.4.4	1.135	0.8172	0.760544931	0.239455069
AVL-0064	40	36	15	5	0.8	0.8	1	0.9	14.7892488	40.91442675	Telaio_8.5.6.5.6	1.0792	0.6216192	0.504347917	0.495652083
AVL-0068	27	15	15	5	1	1	1	0.9	14.78651882	40.91349795	Telaio_5.5.3.5.4.5	1.154	1.0386	1	0
AVL-0072	32.9	25.2	12	4	1	1	0.9	0.9	14.7871494	40.91285455	Telaio_7.4.7.4.7.3.6	1.0001	0.810081	0.751219544	0.248780456
AVL-0074	40.8	15.9	18	6	0.8	0.8	1	0.9	14.78785167	40.91323606	Telaio_8.6.3.5.1.5.3	1.0543	0.6072768	0.485560388	0.514439612
AVL-0078	60	25	9	3	1	1	1	0.9	14.78846946	40.91330713	Telaio_12.3.5.5.5	1.1628	1.04652	1	0
AVL-0079	32.4	15	18	6	0.8	1	1	0.9	14.7852025	40.91295865	Telaio_9.6.3.3.6.5	1.081	0.77832	0.709614881	0.290385119
AVL-0080	32.9	16	12	4	0.8	1	0.9	0.9	14.78763392	40.91291768	Telaio_7.4.4.4.7.4	1.1217	0.7268616	0.642208017	0.357791983
AVL-0083	24	20	18	6	1	1	1	0.9	14.78968391	40.91348905	Telaio_6.6.4.4.5	1.0675	0.96075	0.948585276	0.051414724
AVL-0084	25	18	15	5	1	1	0.9	0.9	14.78597073	40.91300879	Telaio_5.5.3.5.6	1.0728	0.868968	0.828357349	0.171642651
AVL-0085	37.8	13.2	15	5	1	1	0.9	0.9	14.78569158	40.91292535	Telaio_9.5.3.4.2.4.4	1.0927	0.885087	0.849472099	0.150527901
AVL-0089	36	13.8	15	5	1	1	1	0.9	14.78823461	40.91297452	Telaio_9.5.3.4.4.2	1.0964	0.98676	0.982656537	0.017343463
AVL-0090	27	16	21	7	0.8	1	1	1.1	14.78778102	40.91360215	Telaio_9.7.3.4.6	1.0576	0.930688	0.909206183	0.090793817
AVL-0093	37.8	16.8	24	8	0.8	0.8	0.9	0.9	14.79041279	40.91394877	Telaio_9.8.4.4.2.4.2	1.0432	0.54079488	0.398473775	0.601526225

4.4 Display of Results in QGIS (Seismic microzonation Map)

After computing the collapse coefficient for the selected buildings, a dedicated tool was required to visualize the results and to classify buildings at the urban scale. To this end, the open-source Geographic Information System **QGIS** (version 3.34)(QGIS Development Team, 2024) was used. **QGIS** provides a rich set of spatial analysis capabilities and enables the integration of numerical/tabular outputs with map layers, making it suitable for spatial visualization of seismic vulnerability.

4.4.1 Data import and attribute join.

The numerical outputs (including the collapse coefficient and the derived *SafeScore*) computed in MATLAB were exported as structured spreadsheet files and imported into **QGIS**. Since each building was available as a polygonal vector feature with precise geographic coordinates, the analytical attributes were attached to the city map via an attribute *Join* between the building identifier in the shapefile and the spreadsheet.

4.4.2 Symbology and categorical mapping.

Using **QGIS Symbology**, buildings were color-coded into four vulnerability classes according to their SafeScore (or, equivalently, the complementary index $V = 1 - \text{SafeScore}$): *Safe*, *Relatively Safe*, *Moderately Vulnerable*, and *Highly Vulnerable*. Buildings excluded from the analysis (e.g., masonry or steel typologies, or highly irregular plans) were placed in a separate layer and rendered with a hatched pattern so that they are considered in the final map but not mistakenly grouped with the classified RC stock.

4.4.3 Map composition and export.

Using the *Print Layout*, the final map was composed by adding standard cartographic elements—title, legend, scale bar, and north arrow—and exported as a raster image (PNG) and as a PDF for direct inclusion in the thesis.

Figure 4.3 shows the final vulnerability map.

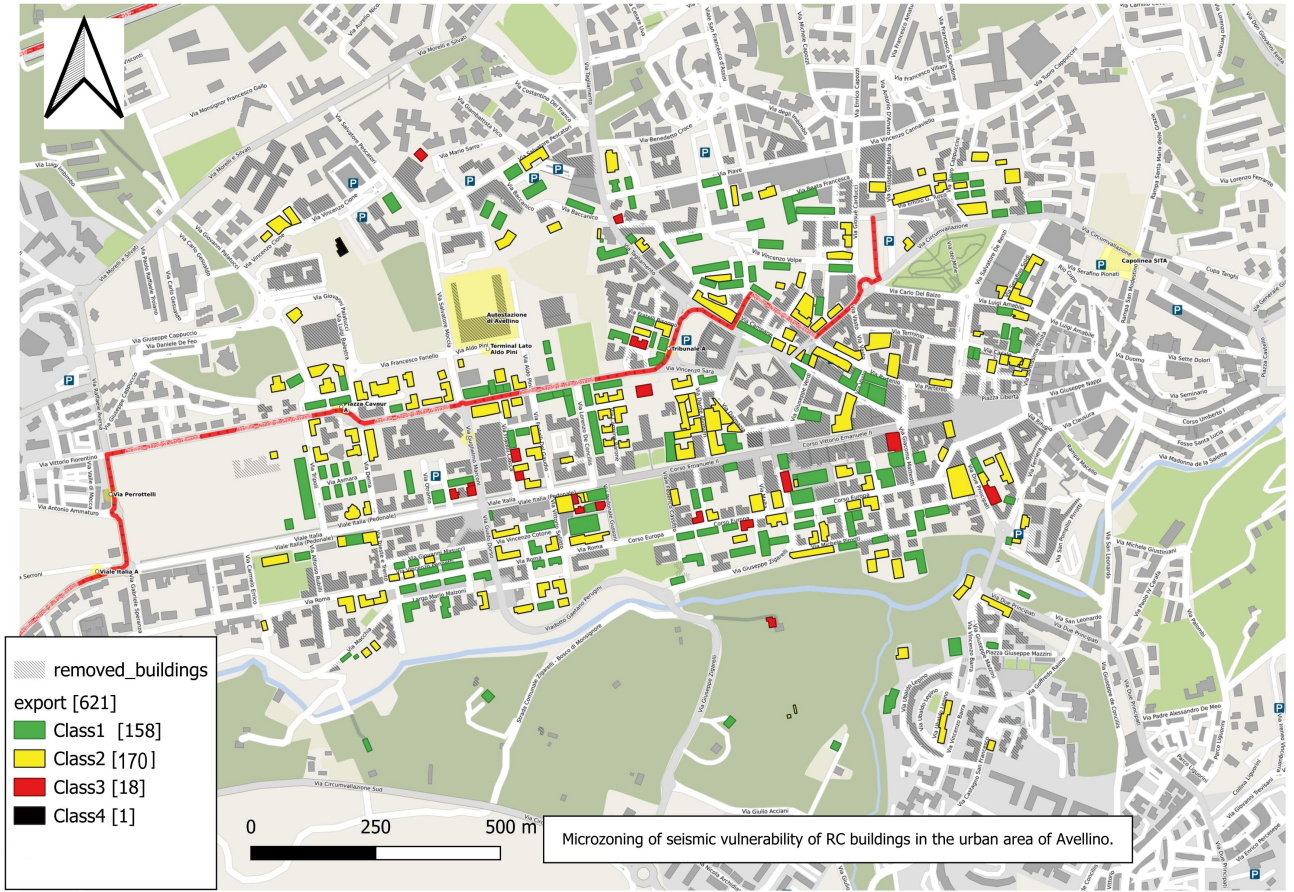


Figure 4.3: Final seismic vulnerability classification map for the central area of Avellino. Buildings are classified from *Safe* (green) to *Highly Vulnerable* (black). Buildings outside the study scope are shown with a hatched fill to visually distinguish surveyed areas from data-sparse zones; the red polyline highlights the main street in the area.

The outcome of this workflow is an urban seismic microzonation map that can be used directly for emergency management, for prioritizing retrofit interventions, and for assessing response capacities. The procedure also provides a reproducible basis for future automation (knowledge extraction), machine-learning pipelines, and broader city-scale risk analyses.

4.5 Statistical Analysis of Vulnerability Results

In this section, a preliminary statistical analysis is carried out to provide a clear picture of the distribution of seismic risk within the urban fabric of Avellino. The analysis is based on numerical outputs obtained from the structural modeling workflow in ANSYS and MATLAB, as detailed in Chapter 3.

Overall, **CC** values were obtained for the RC stock in the study area (**347** records within **624** surveyed buildings): **106** via VFEM/FELA and others via ML prediction. After applying the qualitative and measurable modifiers, each record was assigned to one of four risk levels (see Table 4.4). Figures 4.4 and 4.6 report the distribution of classes.

Table 4.4: Distribution of buildings by vulnerability class.

Class	Count	Percent (%)
Class 1 — Safe	158	45.53
Class 2 — Relatively Safe	170	48.99
Class 3 — Moderately Vulnerable	18	5.19
Class 4 — Highly Vulnerable	1	0.29

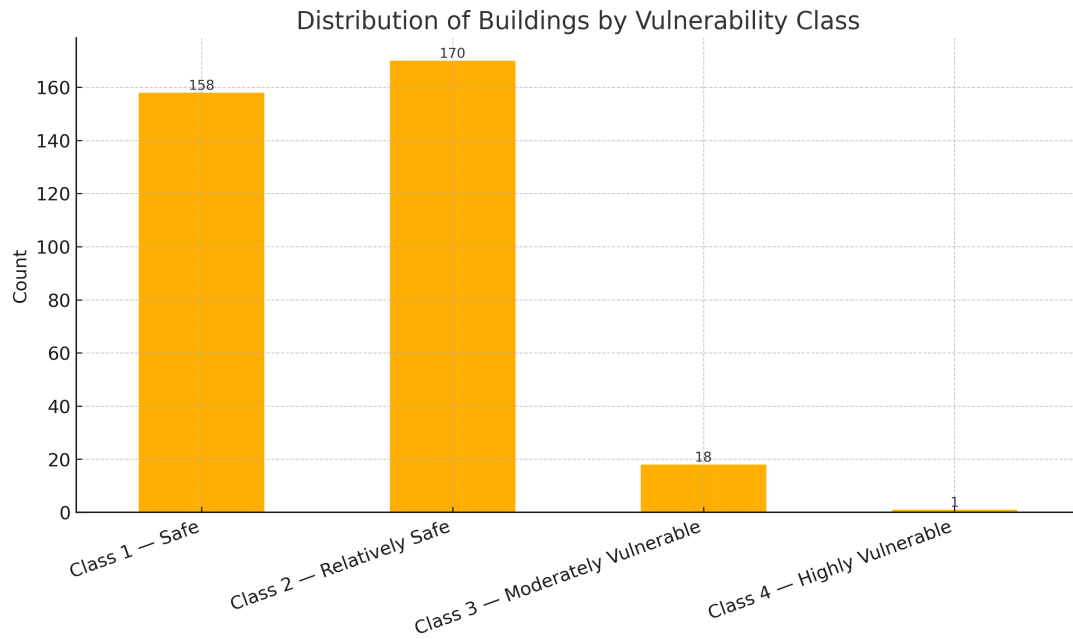


Figure 4.4: Distribution of buildings by vulnerability class (counts).

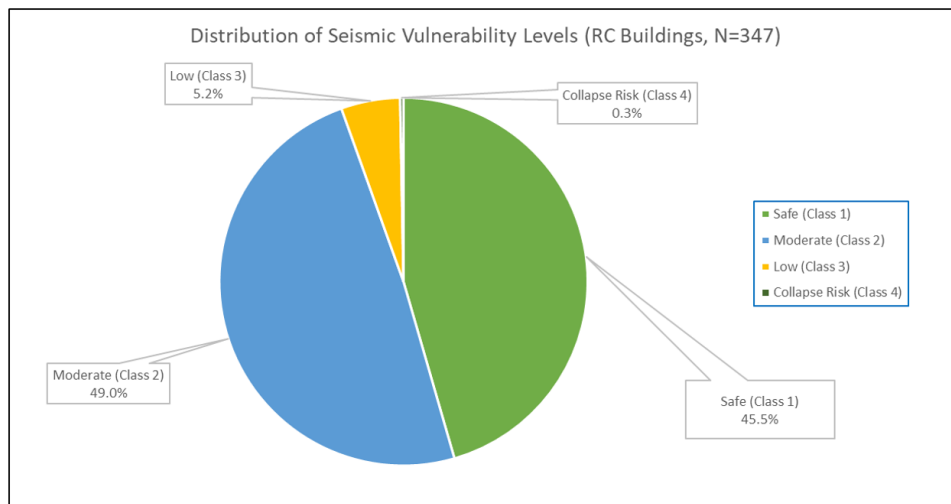


Figure 4.5: Share of buildings by vulnerability class (percentages).

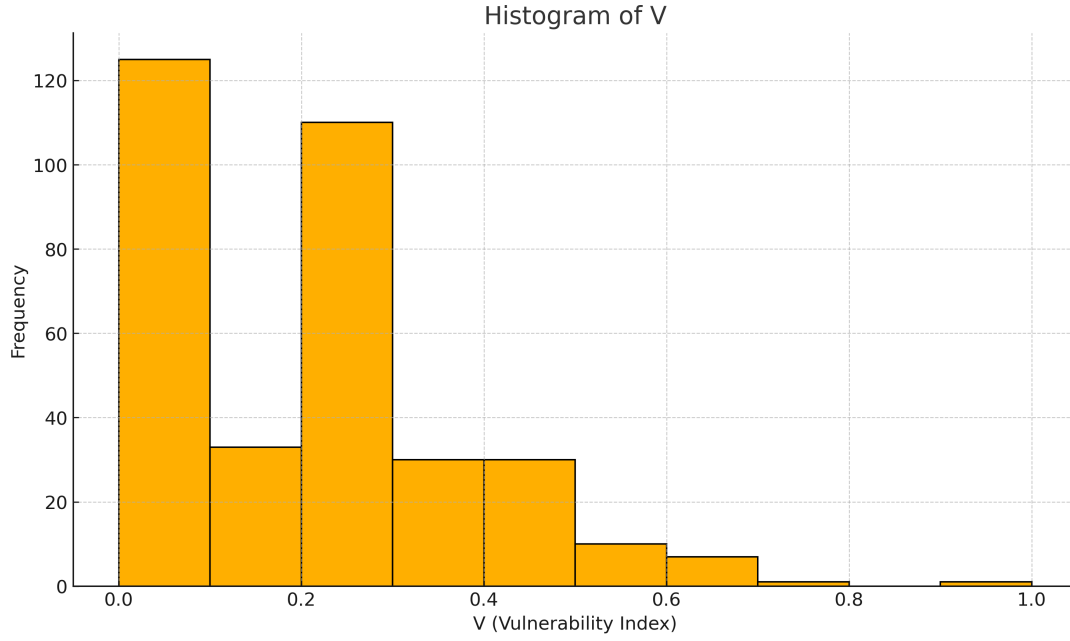


Figure 4.6: Histogram of the vulnerability index V (bin width 0.1).

4.5.1 Correlation between collapse coefficient and number of floors.

A positive association is observed between the **CC** and the number of floors. Pearson's $r = \mathbf{0.24}$ (95% CI **0.14–0.34**) indicates a weak linear relationship, while Spearman's $\rho = \mathbf{0.41}$ suggests a moderate monotonic trend. A simple OLS fit yields

$$\mathbf{CC} = 0.0138 \times \text{Floors} + 1.1383,$$

implying that each additional floor is associated, on average, with a $\sim \mathbf{0.014}$ increase in **CC**. Figures 4.7 and 4.9 visualise the point cloud, distribution per floor count, and mean with 95% confidence intervals.

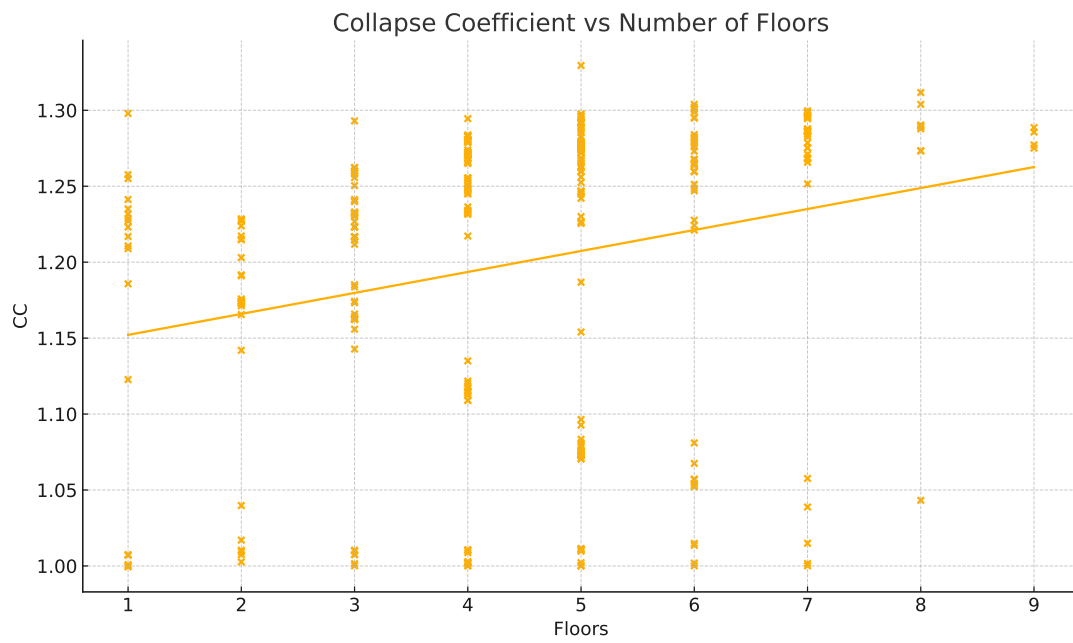


Figure 4.7: Scatter of **CC** versus number of floors with OLS trend line.

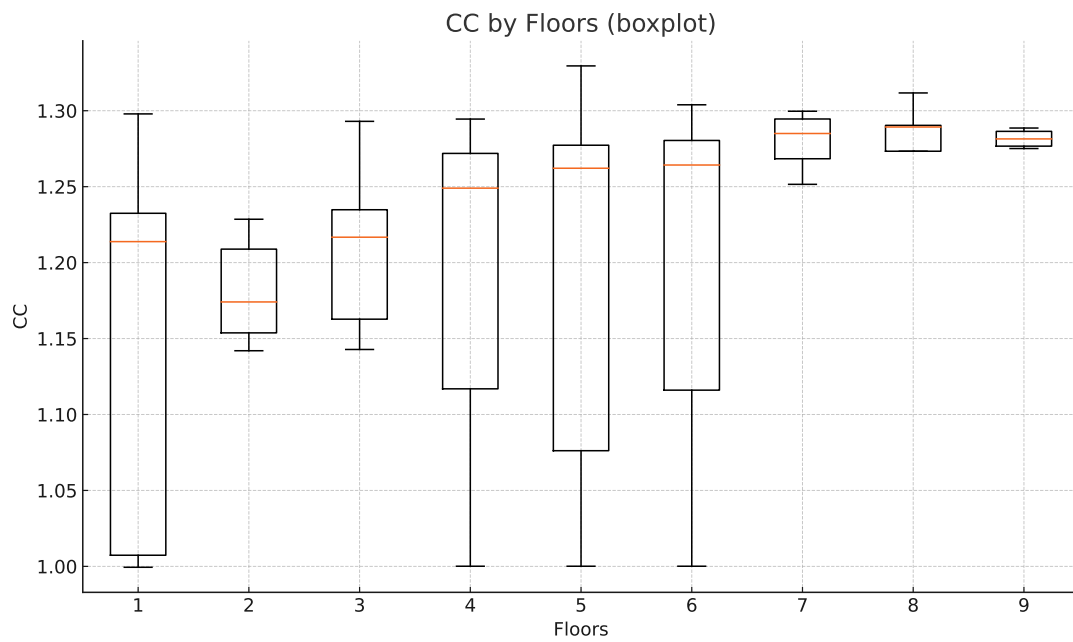


Figure 4.8: Distribution of **CC** by floor count (boxplots without outliers).

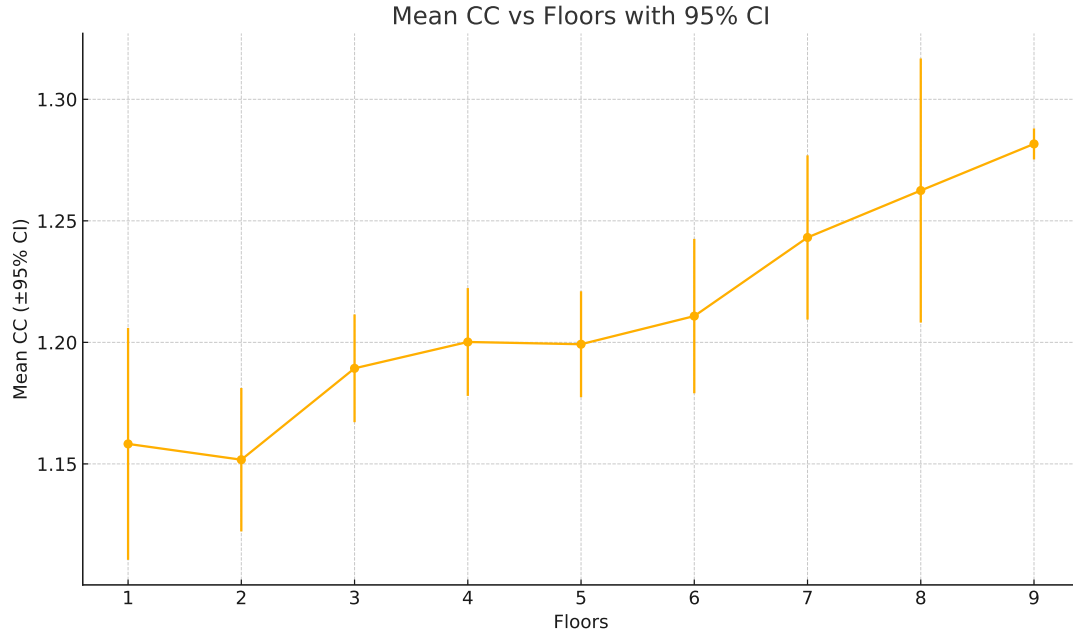


Figure 4.9: Mean **CC** versus floor count with 95% confidence intervals.

4.5.2 Interpretation and implications.

Since larger values of **CC** indicate a larger safety margin (and values closer to 1.0 indicate proximity to the limit state), the observed positive trend suggests that, in this sample, taller RC buildings tend to exhibit a slightly higher collapse coefficient on average. This does *not* imply causality: code era, material quality, regularity, and plan configuration may act as confounders. Consistently, the correlation between the composite vulnerability index V (which includes qualitative modifiers) and floor count is negligible (Pearson $r \approx 0.02$), underscoring that geometric height alone is not a strong predictor once quality indicators are accounted for. From an operational standpoint, the class distributions (Table 4.4) remain the primary driver for prioritizing detailed assessments and retrofit interventions at the urban scale.

Chapter 5

Dataset Construction

In this chapter, the objective and data sources are first described. Then, the process of creating *virtual twins* (VTs), extracting, cleaning, and preparing the data for training *machine learning* (ML) models is presented.

Accounting of assets and models. A total of 6300 virtual twins were generated by preprocessing with the ANSYS program (parametric geometry and features). We excluded 210 assets with complex plans (out of scope of the present work) and 67 non-RC assets (steel, masonry, etc.), retaining 347 RC buildings. Among these, 7 pairs were geometrically identical (different locations but same structural morphotype), yielding 340 unique RC morphotypes to be assessed. For these 340 morphotypes, collapse coefficients (CC) were obtained via a hybrid route: 106 were mechanics-solved with VFEM/FELA, and 234 CC values were predicted by the ML model to enable urban-scale coverage.

Terminology. In this thesis, analyzed/solved refers exclusively to VFEM/FELA computations; predicted/inferred refers to ML outputs.

Table 5.1: Accounting of buildings and virtual twins used in this thesis.

Item	Count
Virtual twins generated (ANSYS pre-processing)	6,300
Real buildings inventoried in the study area	624
Excluded: complex plans (out of scope)	−210
Excluded: non-RC (steel, masonry, others)	−67
RC buildings retained	347
Deduplicated geometric twins (7 pairs)	−7
Unique RC morphotypes (final set)	340
Mechanics-solved with VFEM/FELA (CC computed)	106
ML-predicted CC (for coverage at urban scale)	234

5.1 General Objective of Dataset Construction

The aim of this chapter is to describe the procedure for building a structured database from the analytical results and geometric features of buildings, to be used for training **ML** models. This database is extracted from the **VTs** generated in ANSYS and MATLAB environments. The main objective is to provide accurate data for predicting seismic vulnerability levels through data-driven models and **ML** techniques.

5.2 Data Sources and Sample Categorization

The main data sources include geometric features of the structural models, material properties, beam and column distribution, number of floors, bay lengths, and the final analytical output: the *collapse coefficient* (**CC**). All these data were extracted from ANSYS modeling and MATLAB analysis (GridWork code) and stored in processable file formats.

The final dataset consists of 347 **VT** models of existing *reinforced concrete* (**RC**) buildings in the urban area, of which 106 were fully analyzed. Since a complete analysis of this entire set of around 350 models would be time-consuming, and in search of ways to reduce computation time while preserving result accuracy, **ML** methods were employed. As will be detailed in later chapters, approaches ranging from the simplest to the most advanced **ML** models were tested. Even with the smallest necessary set of complete analyses, by clustering and categorizing structures, it was possible to reach the desired results with an acceptable minimum error.

5.3 Creation of Virtual Twins

In this research, **VTs** refer to a set of numerical structural models systematically generated by combining geometric parameters such as the number of columns, floors, bay spacing, and section dimensions. These models were created in ANSYS (as a preprocessor) and subsequently analyzed in MATLAB using a limit analysis code based on Melan's theorem. Each model represents a specific "morphotype" or structural typology, which can be used for vulnerability classification.

The process of generating these **VTs** included the following steps:

- Automated definition of combinations of structural parameters (number of columns in X and Z directions, number of floors, height of the floors, spacing of the bays).
- Creation of geometric models in ANSYS using predefined macros.
- Extraction of files containing node coordinates, connectivity, material properties, and loading.
- MATLAB analysis to compute collapse loads and extract relevant parameters.
- Output file naming convention designed to encode geometric model information.

For example: `VirtualTWIN_4-2-3-4-5`, where:

- 4: number of bays in X direction
- 2: number of floors
- 3: number of bays in Z direction
- 4: bay spacing in X direction (m)
- 5: bay spacing in z direction (m)

The sections dimensions in most models were set to 60 cm by 40 cm.

Figs. 5.1 to 5.3 show examples of **VTs** at different modeling stages.

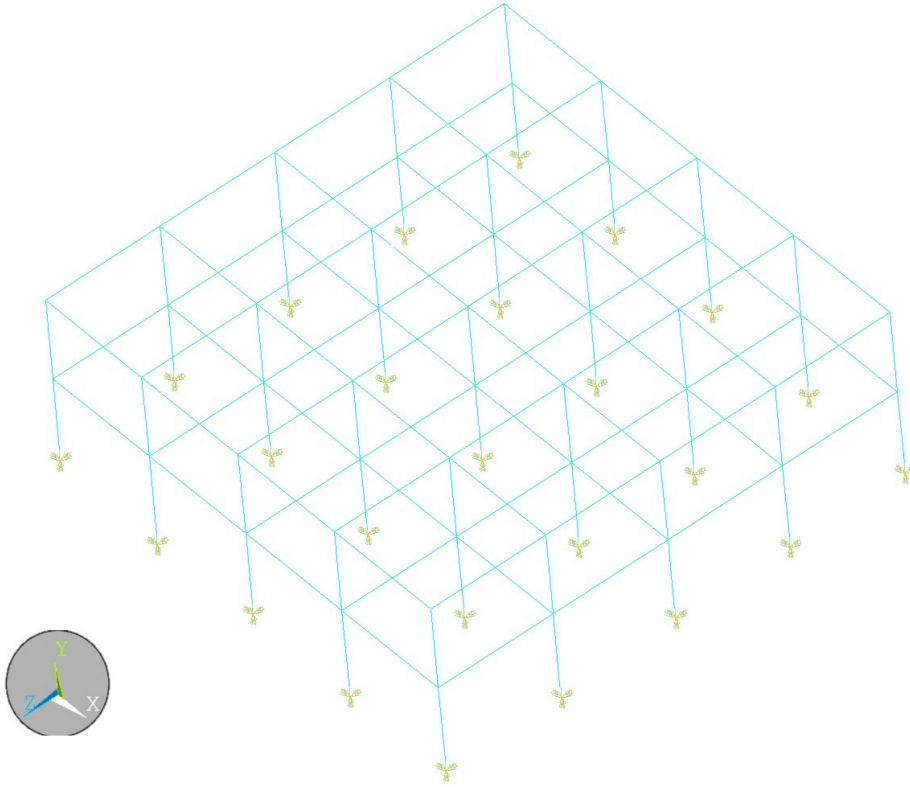


Figure 5.1: 3D view of a **VT** in the preprocessing stage.

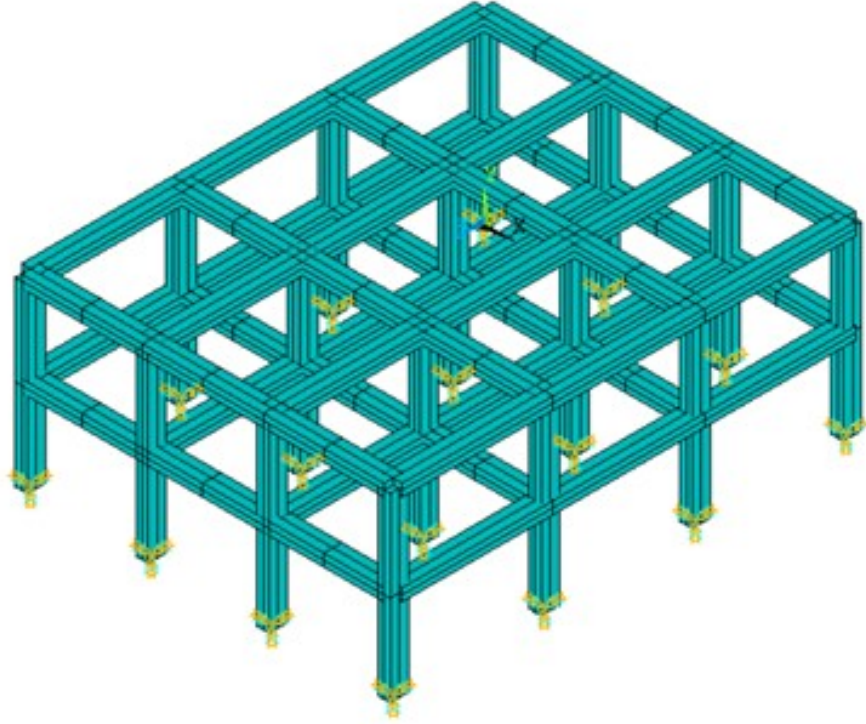


Figure 5.2: 3D view of a **VT** with 40 cm $\times$ 60 cm section dimensions.

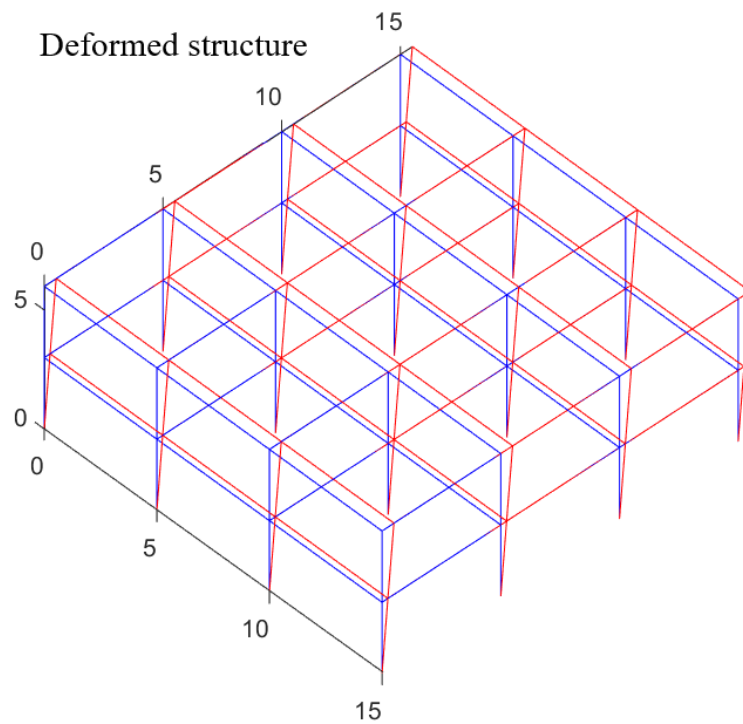


Figure 5.3: 3D view of a **VT** in MATLAB analysis stage. Example: Telaio_3.2.3.5_5.

The above figure corresponds to the **VT** named `Telaio_3.2.3.5_5`, representing a two-story structure with spans of 5 meters in both directions and three bays on each side. The numbers shown are expressed in meters.

5.4 Feature Categorization

Features of each sample include parameters obtained from geometric and structural modeling in ANSYS and MATLAB. These features are divided into two main categories:

Inputs:

- Number of bays in X (n_x) and Z (n_z) directions
- Number of floors (n_s)
- Bay lengths (l_x, l_z)
- Beam and column section dimensions ($B_1, H_1, A_1, \dots$)
- Material properties such as concrete strength and moment of inertia

Outputs:

- **CC**: the ultimate collapse load and elastic load in three principal directions are computed, yielding six intermediate outputs. The smallest ratio of collapse to elastic load in the two horizontal directions is taken as the final output, denoted as the minimum seismic collapse coefficient.

5.5 File Structure and Preprocessing

To convert raw results into the final dataset, an initial preprocessing stage was performed. Data were extracted from MATLAB output files and converted into formats suitable for **ML** environments such as CSV or JSON. Missing values, numerical noise, and inconsistencies were checked and corrected. Feature normalization was also applied to improve **ML** model performance.

5.6 Validity and Diversity of Data

The geometric structure of these **VTs** includes a wide range of combinations in bay spacing, number of columns, and number of floors. This diversity enables the trained **ML** model to generalize to various building types.

5.7 Advantages of Synthetic Data

One strength of this dataset is full control over model features and data reproducibility. Unlike field data, which are often incomplete and ambiguous, data from numerical modeling are precisely and completely defined, making them ideal for **ML**.

5.8 Storage and Final Format

The data are stored in an Excel file containing 13 columns and 106 rows, each representing a complete structural model with its features and output label. This file is ready for training supervised learning models in environments such as scikit-learn or TensorFlow.

Table 5.2 shows a sample of validated structural model data, including elastic and collapse loads in three cases, along with geometric specifications. These form the basis for **ML** in Chapter 8.

Table 5.2: Sample validated structural model data (partial list).

Model	n_x	n_y	n_z	l_x	l_z	PE	SE _x	SE _z	PC	SC _x	SC _z	CC
Telaio_5_5_3_8_5	5	5	3	5.00	4.50	2133.88	925.95	141.15	2463.48	1231.01	320.91	1.3295
Telaio_7_5_2_4_6_5_5	7	5	2	4.60	5.50	1648.90	759.90	140.48	1776.03	823.31	308.27	1.0834
Telaio_2_7_7_7_5	2	7	7	7.00	5.00	1843.43	666.34	86.16	1866.64	864.31	86.17	1.0001
Telaio_4_5_8_4_4	4	5	8	4.00	4.00	1416.76	554.77	148.26	1557.76	600.71	148.28	1.0001
Telaio_10_5_4_5_4	10	5	4	5.00	4.00	1801.76	916.30	137.30	1926.43	990.64	292.50	1.0811
Telaio_8_4_3_6_7	8	4	3	6.00	7.00	2188.69	1233.03	205.34	2251.94	1537.24	489.42	1.2467
Telaio_8_2_2_5_4_5	8	2	2	5.00	4.50	1783.46	2640.90	678.77	1832.44	3100.61	1656.03	1.1741
Telaio_7_3_5_5_5_5	7	3	5	5.50	5.00	2001.79	1690.72	341.93	2045.82	2053.25	689.36	1.2144
Telaio_10_1_6_5_5	10	1	6	5.00	5.00	1744.20	5432.99	2031.64	1798.29	6041.10	2031.69	1.0000
Telaio_9_2_4_4_5	9	2	4	4.00	5.00	1436.26	1725.54	678.92	1553.17	2055.07	1664.49	1.1910

The final combined dataset, with complete descriptions, is presented in Appendix B.

Chapter 6

Analysis of Results and Vulnerability Classification

6.1 Introduction and Objectives of Results Analysis

After constructing the structural dataset and performing limit analyses for a selected subset of existing buildings within the study area, the next step is the interpretation and classification of results to enable a comprehensive assessment of seismic vulnerability. In this chapter, a combination of quantitative parameters (such as loading conditions and collapse coefficient) and qualitative attributes (including age, maintenance condition, plan irregularity, and elevation regularity) are employed to determine the relative seismic risk level of each building.

The primary objective of this chapter is to integrate analytical outcomes with cognitive and descriptive features of the structures, thereby achieving a realistic and reliable classification of their vulnerability levels. Such a classification can serve as a valuable tool for crisis management planning and prioritizing retrofitting interventions. To this end, the classification criteria are first introduced, followed by a statistical examination of their distribution across the dataset. Furthermore, graphical illustrations and correlation analyses between geometric, qualitative, and structural features are presented.

It should be noted that, unlike Chapter 8—which focuses on data-driven modeling and the training of *machine learning* (ML) models based on numerical parameters—this chapter aims to utilize all available information (including both data obtained from numerical analyses and data generated through ML) in order to provide a holistic overview of the seismic vulnerability of the studied structures. The outcomes of these analyses will also form a solid foundation for validating intelligent models in subsequent stages.

6.2 Criteria for Vulnerability Level Classification

For a comprehensive analysis of building seismic vulnerability, this chapter employs a set of quantitative and qualitative parameters, all of which are categorized and grouped in the following phases. These parameters include:

- **Quantitative indicators derived from limit analyses:** covering permanent and seismic loading in two principal directions, as well as the calculation of the *collapse coefficient* (CC) for each structural model.
- **Qualitative attributes influencing seismic performance:** such as building age, seismic design code level, maintenance condition, plan irregularity, and elevation regularity.

By combining these characteristics, a final vulnerability level is defined for each building, which serves as the basis for the statistical and comparative analyses presented in this chapter. Unlike the data-driven approach adopted in **ML** models (see Chapter 8), the classification developed here does not rely solely on numerical parameters. Instead, it seeks to integrate all relevant factors—both analytical and qualitative—to provide an assessment that closely reflects the actual seismic vulnerability level of the buildings.

6.3 Statistical Analysis of Seismic Vulnerability Classification Results

Based on the adopted classification criteria, buildings within the study area were categorized into four seismic vulnerability levels, consistent with engineering practices and international guidelines. This classification is grounded on the SafeScore index, which synthesizes both analytical and qualitative parameters:

- **Class 1 (Safe):** Buildings with high seismic capacity and low vulnerability risk.
- **Class 2 (Moderate):** Buildings that generally satisfy seismic performance requirements but may be exposed to moderate levels of risk.
- **Class 3 (Low):** Buildings exhibiting noticeable weaknesses in seismic capacity, with a higher likelihood of sustaining damage.
- **Class 4 (Collapse Risk):** Buildings with severe seismic deficiencies and a high probability of collapse during strong earthquakes.

This four-level taxonomy (SafeScore-based) and the map symbology/class thresholds are *adapted from* (Zona et al., 2025).

The distribution of seismic vulnerability levels for the analyzed RC buildings ($N = 347$) is illustrated in Fig. 6.1.

- Class 1 (Safe): 158 buildings (45.53%)
- Class 2 (Moderate): 170 buildings (48.99%)
- Class 3 (Low): 18 buildings (5.19%)
- Class 4 (Collapse Risk): 1 building (0.29%)

This distribution shows that the majority of buildings in the study area fall within safe or moderate levels, while only a very limited proportion of structures are classified as highly vulnerable. The single building at risk of collapse highlights the necessity of prioritizing retrofitting actions for such extreme cases, given their disproportionate contribution to potential seismic losses.

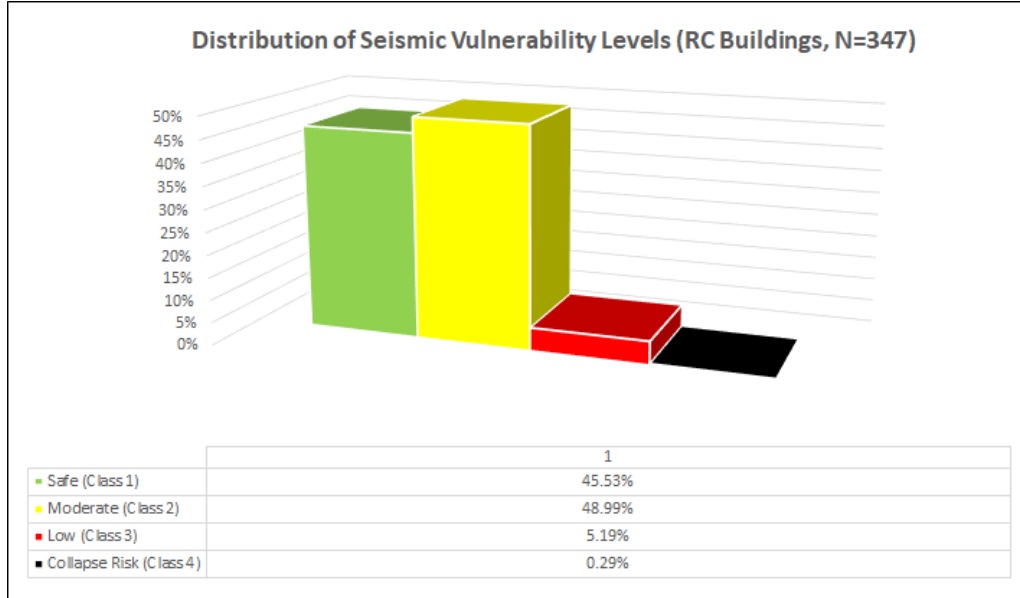


Figure 6.1: Distribution of Seismic Vulnerability Levels for All RC Buildings (N = 347)

6.4 Spatial Analysis and Vulnerability Mapping

To illustrate the spatial distribution of seismic vulnerability levels, the final classification results for all 347 analyzed buildings within the study area were mapped using *quantum geographic information system* (QGIS). Each building was color-coded according to its corresponding vulnerability class, as follows:

- **Green** → **Class 1 (Safe)**: 158 buildings
- **Yellow** → **Class 2 (Moderate)**: 170 buildings
- **Orange** → **Class 3 (Low)**: 18 buildings
- **Red** → **Class 4 (Collapse Risk)**: 1 building

The spatial pattern clearly indicates that highly vulnerable buildings (particularly those in Classes 3 and 4) are mostly concentrated in older districts of the city. These areas are characterized by irregular street layouts, aging construction stock, and limited retrofitting interventions, which increase their exposure to seismic risk. In contrast, newer residential zones and recently developed neighborhoods show a predominance of buildings classified as safe or moderate.

This map serves as a key instrument for urban seismic microzonation and can effectively guide decision-makers in prioritizing retrofitting measures and emergency management planning.

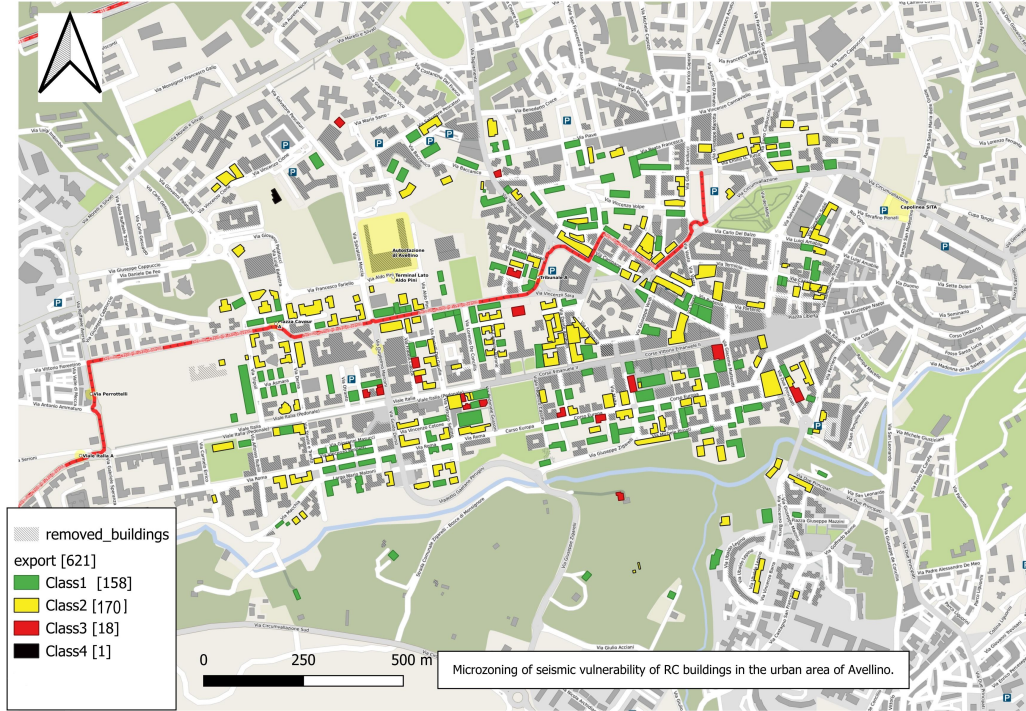


Figure 6.2: Seismic Vulnerability Microzonation of RC Buildings in the Urban Area of Avellino

6.5 Statistical Analysis of Factors Influencing Seismic Vulnerability

In order to deepen the interpretation of seismic vulnerability results, this section evaluates the influence of four main qualitative parameters—age, elevation regularity, maintenance condition, and plan irregularity—on the final classification results. The analysis is based on cross-tabulations and correlation graphs (Fig. 6.3) that highlight the contribution of each factor to the vulnerability levels.

- **Building Age:** The results show that older buildings, particularly those constructed before the enforcement of modern seismic codes, exhibit significantly higher vulnerability. More than 70% of the pre-code buildings fall into the “Moderate” or “Low” vulnerability classes, while only 18% are categorized as “Safe.” In contrast, post-code structures demonstrate a notably higher proportion of buildings classified as safe.
- **Elevation Regularity:** A similar trend was observed: buildings with severe elevation irregularities (0.65) were exclusively classified as Class 4 (Collapse risk), while those with moderate irregularity (0.80) constituted a large portion of Class 2 (Moderate) and Class 3 (Low) buildings. In contrast, buildings without elevation irregularity (1.00) were predominantly assessed as Safe (Class 1) or Moderate (Class 2).

- **Maintenance Condition:** Poorly maintained buildings have substantially higher probability of belonging to “Low” or “Collapse Risk” classes, with 36% of them showing deficiencies that critically affect seismic performance. In contrast, well-maintained buildings are predominantly distributed in the “Safe” and “Moderate” categories, confirming the importance of continuous structural maintenance.
- **Plan Irregularity:** The results indicate that buildings with irregular plans are disproportionately represented in the higher vulnerability classes, particularly “Moderate” and “Low.” Regular-plan structures, on the contrary, display a much safer profile, with the majority falling within the “Safe” category.

In general, these findings highlight the significant role of qualitative parameters in shaping the seismic vulnerability profile of the building stock. When combined with analytical outcomes, they enable a more holistic and realistic classification framework, bridging the gap between structural performance and urban-scale vulnerability assessment.

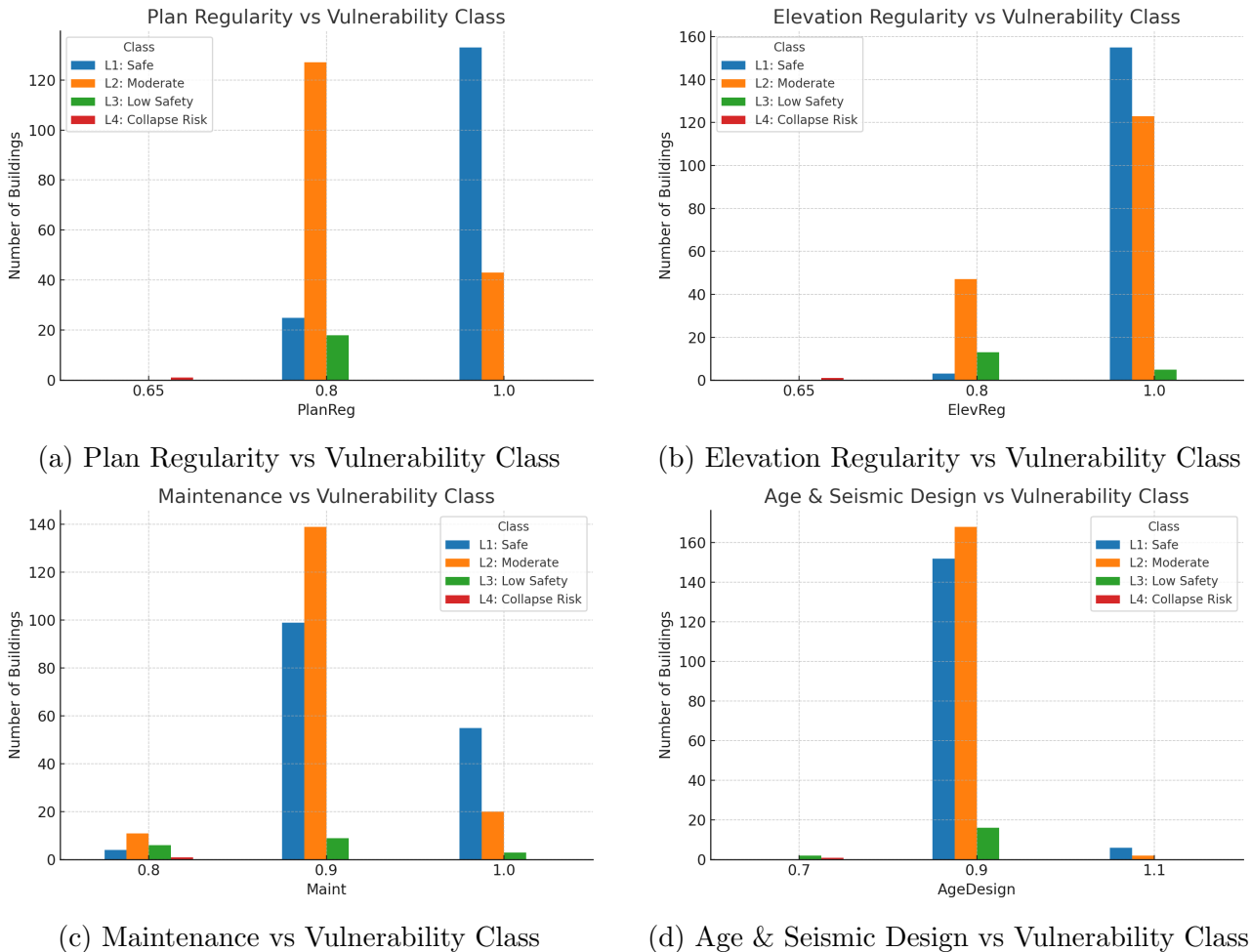


Figure 6.3: Role of qualitative factors in determining the seismic vulnerability level of structures.

Chapter 7

Validation

In this chapter, to examine the reliability and accuracy of the developed method, we compare its outcomes against two well-established models in the literature: the macroseismic approaches by *Ferreira et al. (2020)* and *Lagomarsino & Giovinazzi (2006)*. Both models are grounded in empirical seismic data and establish relationships between earthquake intensity and observed building damage.

A key commonality between these references and the proposed method is the use of the *Mean Damage Grade* (μ_D) as the final indicator of vulnerability. This enables matching the output of the present model to those references and assessing discrepancy, deviation, and accuracy through numerical and conceptual comparison.

Below, we first give a brief overview of the theoretical background and mathematical structure of each reference, and then compare their outputs with those of the proposed model.

7.1 Introduction to the Macroseismic Model by Ferreira et al. (2020)

In recent years, macroseismic models for rapid, large-scale assessment of building seismic vulnerability have attracted significant attention. Among them, the model by Ferreira and colleagues is a successful example that combines a semi-empirical approach with statistical analysis of observed earthquake damage. Its main goal is to provide a simple, city-scale method, aligned with the EMS-98 intensity scale, to estimate the mean damage grade (μ_D) for different seismic scenarios.

The model is based on an analytical relationship between seismic intensity (I) and a building vulnerability index (I_v). The index I_v is determined from eight qualitative parameters—building age, height, geometric irregularity, use type, urban context location, material, seismic design level, and maintenance condition. Each parameter is weighted, and I_v is computed as a weighted sum. This numerical index (0–100) is inserted into the main equation to estimate μ_D :

$$\mu_D = 2.839 \left[1 + \tanh \left(\frac{I + 10.79 V - 11.6}{5} \right) \right], \quad (7.1.1)$$

where V is derived from I_v as

$$V = -0.02 + 0.0104 I_v. \quad (7.1.2)$$

The output μ_D ranges from 0 (no damage) to 5 (complete collapse). This model has shown good consistency with empirical data in several European countries and has been widely applied to urban seismic microzonation.

7.2 Introduction to the Macroseismic Model by Lagomarsino & Giovinazzi (2006)

A well-known and widely used macroseismic model is that by Lagomarsino & Giovinazzi (2006), developed within the European *Vulnerability Index Method* and adopted for rapid loss estimation in past and future earthquakes. Its advantages include simple relations, ease of calibration with empirical data, and consistency with EMS-98.

Here, the building vulnerability index V is defined in $[0, 1]$ (0: very resistant; 1: very vulnerable) and is usually estimated from structural type, seismic design quality, building height, and construction age. The mean damage grade is given by:

$$\mu_D = 2.5 \left[1 + \tanh \left(\frac{I + 6.25 V - 13.1}{Q} \right) \right], \quad (7.2.1)$$

where I is EMS-98 intensity, $V \in [0, 1]$, and Q is a quality factor (typically 2.3 to 2.6 for RC buildings). The output μ_D again varies from 0 (no damage) to 5 (complete collapse) and can be calibrated against observed evidence. The model is used in many urban risk projects and international initiatives such as RISK-UE.

7.3 Comparative Analysis of μ_D Between the Proposed Model and References

To evaluate the accuracy of the proposed model, the mean damage grade μ_D was computed for five intensity levels $I = 6$ to $I = 10$ and compared with the results of Ferreira et al. (2020) and Lagomarsino & Giovinazzi (2006).

Fig. 7.1 shows that the trend of μ_D versus intensity is similar between the proposed model and Ferreira's model, with both curves increasing as intensity rises. However, the proposed model yields slightly higher μ_D values, indicating a more conservative damage estimate.

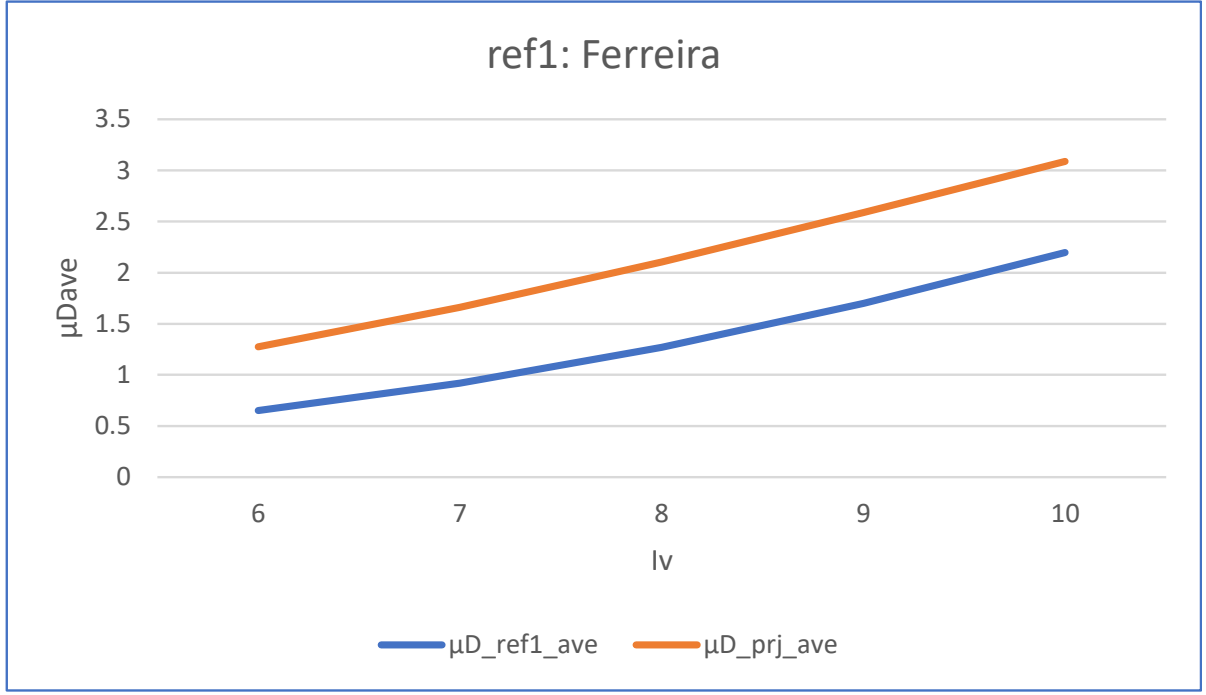


Figure 7.1: Comparison of mean damage grade μ_D between the proposed model and Ferreira et al. (2020). Both show similar increasing trends with intensity; the proposed model is slightly more conservative.

Fig. 7.2 indicates that, compared with Lagomarsino's model, the proposed model preserves the increasing trend but yields uniformly lower μ_D values. This difference may arise from specific characteristics of the case-study dataset (structural system, construction quality, and the parametrization used in V_{model}).

Overall, similarity in the trend and curve shape across both comparisons supports the consistency of the proposed method with established macroseismic approaches, though observed numerical differences warrant further analysis in the following validation section.

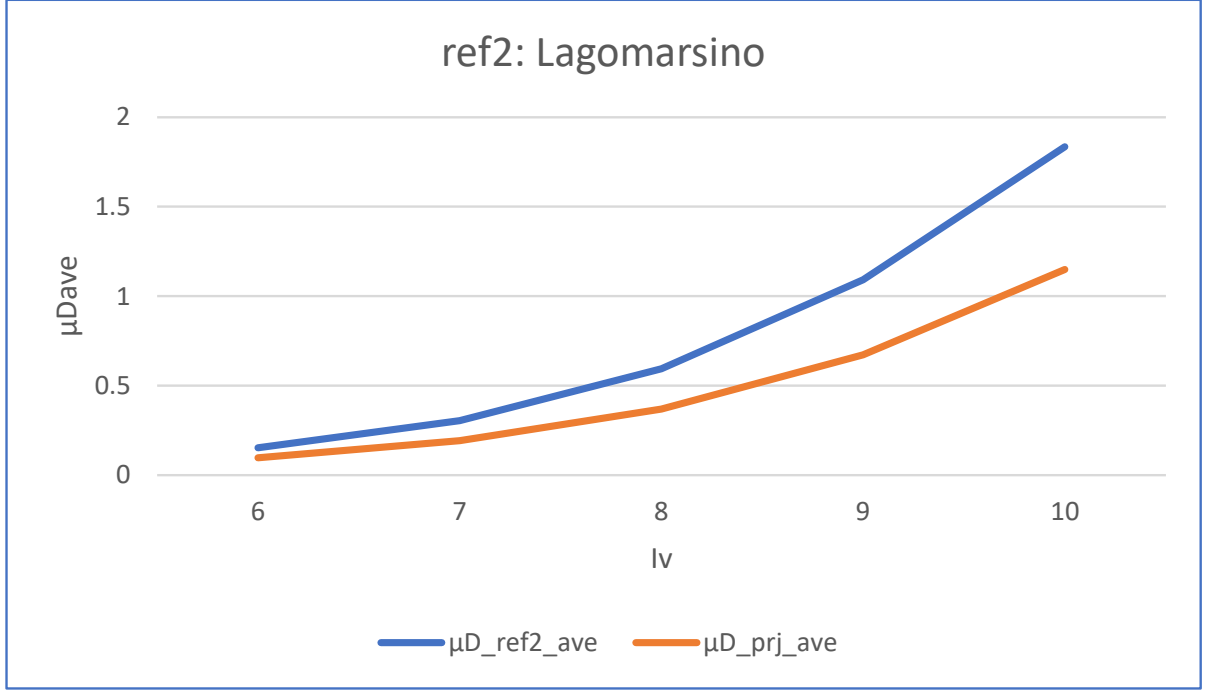


Figure 7.2: Comparison of mean damage grade μ_D between the proposed model and Lagomarsino & Giovinazzi (2006). The overall increasing trend is preserved, while the proposed model produces lower μ_D values.

7.4 Deviation, Conceptual and Numerical Fit Analysis

To quantitatively assess the proposed model against Ferreira and Lagomarsino, four statistical indicators were computed for μ_D over $I = 6 \dots 10$: Mean Absolute Error (MAE), Standard Deviation of Error (SD), Maximum Absolute Error (Max Error), and Pearson's correlation coefficient (R):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\mu_{D_i}^{\text{model}} - \mu_{D_i}^{\text{ref}}|, \quad (7.4.1)$$

$$\text{SD} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n ([\mu_{D_i}^{\text{model}} - \mu_{D_i}^{\text{ref}}] - \overline{\text{Error}})^2}, \quad (7.4.2)$$

$$\text{Max Error} = \max(|\mu_{D_i}^{\text{model}} - \mu_{D_i}^{\text{ref}}|), \quad (7.4.3)$$

$$R = \frac{\text{Cov}(\mu_D^{\text{model}}, \mu_D^{\text{ref}})}{\sigma_{\text{model}} \sigma_{\text{ref}}}. \quad (7.4.4)$$

Interpretation of results.

Ferreira: MAE spans 0.674–1.043 with an increasing trend at higher intensities. The correlation R drops from 0.359 at $I=6$ to -0.089 at $I=10$, indicating loss of correlation at high intensity.

Table 7.1: Comparison metrics of the proposed method with Ferreira and Lagomarsino.

Reference	I	MAE	SD	Max Error	R
Ferreira	6	0.674	0.741	3.120	0.359
Ferreira	7	0.811	0.843	3.102	0.318
Ferreira	8	0.925	0.915	3.183	0.282
Ferreira	9	0.995	0.943	3.093	0.251
Ferreira	10	1.043	0.972	3.281	-0.089
Lagomarsino	6	0.094	0.100	0.899	0.361
Lagomarsino	7	0.183	0.184	1.496	0.414
Lagomarsino	8	0.340	0.313	1.912	0.448
Lagomarsino	9	0.583	0.488	1.785	0.439
Lagomarsino	10	0.878	0.686	1.595	0.389

SD and Max Error are relatively large at higher intensities, suggesting reduced accuracy there. **Lagomarsino:** MAE values are noticeably smaller (0.094–0.878), reflecting lower numerical discrepancy. R remains positive and fairly stable (0.361–0.448) across intensities, indicating sustained correlation. SD and Max Error are smaller than in Ferreira, implying more stability and less deviation.

Summary.

The proposed model reproduces the overall increase of damage with intensity and shows better numerical agreement with Lagomarsino, while discrepancies grow at higher intensities ($I = 9, 10$). These differences are understandable within modeling assumptions and data heterogeneity. Overall, validation against both references indicates adequate performance, aligned with the goal of a fast, practical tool for vulnerability assessment of RC buildings.

It should be noted that direct comparison with the six-level EMS-98 classification was not performed, because the proposed model is formulated within a four-level framework tailored to the project’s rapid-assessment objectives. Nonetheless, cross-checks with the two references indicate that the overall behavior is consistent with accepted macroseismic trends.

Chapter 8

Machine Learning for Urban-Scale Seismic Vulnerability Prediction

8.1 Rationale for Using *machine learning* (ML) at Urban Scale

Following the mechanical modeling and the computation of the *collapse coefficient* (**CC**), the main challenge in scaling the assessment to the urban level is the time and computational cost of detailed structural analyses. While the mechanical pipeline (geometric modeling, preprocessing in ANSYS, and limit analysis in MATLAB) delivers reliable **CC** values, applying it building-by-building across a city is not practical.

ML is adopted as a complementary, data-driven layer to overcome this barrier. By training on a limited set of buildings with reliable **CC** labels, the **ML** model can predict **CC** for the remaining stock using only geometric descriptors, thereby enabling fast, city-scale mapping. This chapter presents the dataset strategy, the models considered, the training/testing design, quantitative results, and the outlook toward integrating real-world data and explainability.

8.2 Data and Clustering Strategy

The reference dataset consists of **347** existing *reinforced concrete* (**RC**) buildings collected in a representative urban area. Geometric and structural descriptors were extracted from maps and *geographic information systems* (**GIS**) (Google Maps, *quantum geographic information system* (**QGIS**)). Running the full mechanical analysis on all 347 buildings was infeasible; therefore, a staged strategy was adopted.

An initial random split (about 30 % train, 70 % test) selected roughly 104–106 buildings for detailed analysis. Early results revealed systematic issues: due to insufficient representativeness, the models sometimes predicted taller buildings (e.g., 7 floors) similar to 5–6 floor cases despite different spans and column counts. The root cause was the lack of representative coverage across the design space, which led the learner to rely on nearest seen examples.

To address this, we replaced the random split with a *clustering-based* selection. Buildings were clustered using geometric/structural features, and one representative per cluster was chosen for full mechanical analysis. In the first pass, **12** representatives were analyzed. To improve coverage, a few additional samples were added in under-represented clusters. In parallel, we leveraged an independent set of **94** buildings with complete mechanical analyses as a backbone. After de-duplication, the final labeled set comprised **106** samples. This strategy reduces cost while preserving diversity, and it aligns with recent evidence that representative selection via clustering improves scalability and coverage in **ML** pipelines (R. Wang & Li, 2025) and is effective in building-related civil engineering tasks (Demetriou et al., 2024).

8.3 Machine-Learning Algorithms

We evaluated three supervised-learning models to predict **CC** from geometric features:

Linear Regression (LR).

A transparent baseline that assumes linear relations between inputs and **CC**. It is fast and interpretable, but limited for nonlinear behavior.

Random Forest (RF).

An ensemble of decision trees that captures nonlinearities and provides feature importance, typically more accurate than LR at the cost of higher complexity.

XGBoost (XGB).

A gradient-boosting approach that iteratively corrects residual errors, with regularization and strong nonlinear modeling capacity—the most accurate in our comparisons.

Table 8.1: Algorithm overview (qualitative).

Model	Class	Pros	Cons	Role
Linear Regression	Linear	Simple, fast, interpretable	Poor at capturing nonlinear effects	Baseline
Random Forest	Ensemble	Captures nonlinear relations; robust to overfitting; feature importance	Heavier than LR	Mid-level
XGBoost	Boosting	High accuracy; regularization; efficient training	Hyperparameter tuning complexity	Best performer

8.4 Training and Model Selection

The training/testing process evolved from a naive random split to a clustering-based design. After clustering, we selected cluster representatives and first performed full mechanics analyses on **12** buildings. We also incorporated an independent set of **94** fully analyzed buildings to strengthen training and enable generalization to the entire **347**-building stock at limited computational cost. The final labeled dataset comprised **106** buildings. Model training and selection were carried out using **stratified 5-fold cross-validation** on these 106 labeled samples. In each fold, the data were split into training and validation subsets in a stratified manner, preserving the balance of the target variable and key features. All preprocessing steps (missing value imputation, normalization, and categorical encoding) were performed *within each fold* to avoid data leakage. Three families of algorithms—**Linear Regression**, **Random Forest**, and **XGBoost**—were compared, and the decision rule followed a risk-aware ranking: **minimize CV-RMSE** (primary); in case of near ties, prefer the model with higher R^2 ; if still tied, choose the one with lower MAE (Figure 8.1). According to the results, **XGBoost**, with a slight but consistent advantage over its competitors, was selected as the final model (see Table 8.2). In the last step, the selected model was refitted on all 106 labeled samples and employed to predict the collapse coefficient (CC) of the entire stock of **347** buildings (Chapter 6).

Evaluation Metrics.

For high-stakes predictions such as seismic vulnerability, the choice of error metric is crucial. We prioritize the **root mean squared error (RMSE)** because it heavily penalizes large deviations that could lead to underestimating the risk of vulnerable structures. As a complementary, scale-independent indicator of overall fit, the **coefficient of determination** (R^2) is used as the first tie-breaker; for completeness, **MAE** is also reported and serves as a secondary tie-breaker.

Table 8.2: Evaluation on the baseline 106 labeled buildings (initial pipeline).

Model	CV-MAE	CV-RMSE	CV- R^2
Linear Regression	0.0602	0.0782	0.3796
Random Forest	0.0231	0.0434	0.7923
XGBoost	0.0247	0.0422	0.7970

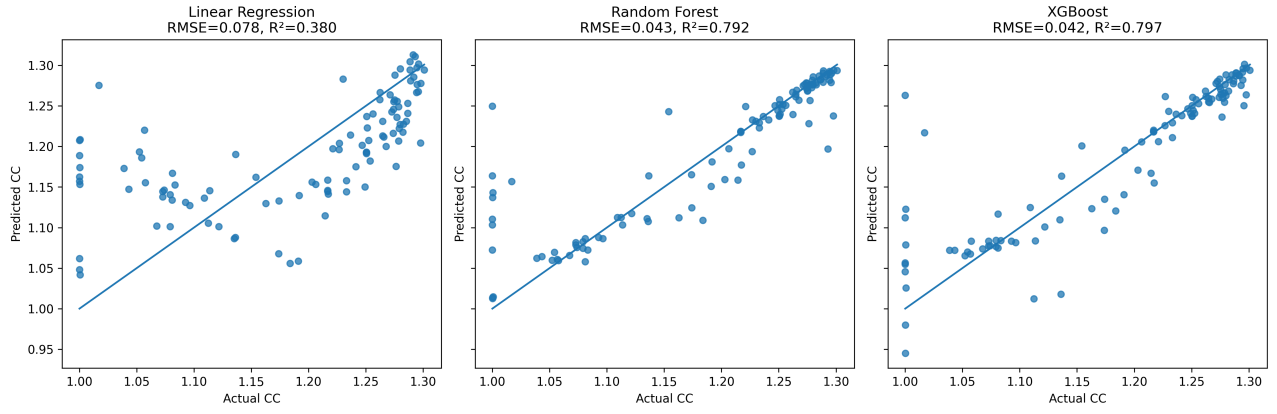


Figure 8.1: Predicted vs. Actual **CC**. The 45° line indicates perfect agreement.

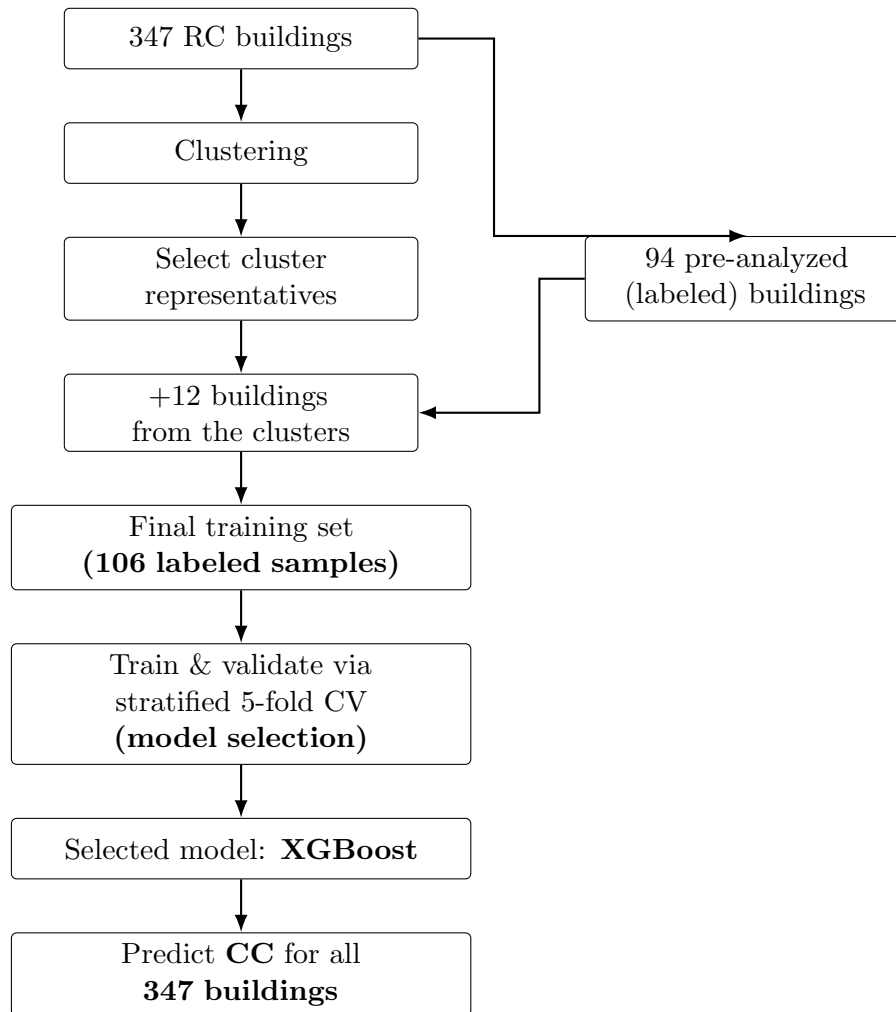


Figure 8.2: Clustering-based workflow for **ML** prediction of **CC**.

8.5 Outlook: Integrating Virtual Twins with Real-World Data

A natural next step is to enrich the feature set and validate against external field data. We will incorporate qualitative/contextual factors such as *building age*, *maintenance condition*, *plan/height irregularities*, and *code era*, extracted either directly from urban registries or via proxies from imagery and **GIS** layers. Careful encoding (e.g., ordinal for code era; target encoding with in-fold validation for nominal variables) can reduce leakage and omitted-variable bias.

For external validation, datasets like *Copernicus EMS—Zagreb 2020* provide an independent benchmark of damage grades. By mapping our four-level vulnerability classification to EMS grades, we can calibrate thresholds and test cross-city generalization. Where distributions shift, domain adaptation with limited target labels is a practical route.

To preserve transparency, we will deploy explainability tools (e.g., SHAP (Lundberg & Lee, 2017)) to provide both global and local attributions, and we will enforce monotonic constraints consistent with structural intuition (e.g., *ceteris paribus*, increasing floor count should not increase **CC**). A succinct *model card* will document scope, assumptions, limitations, and performance.

Uncertainty quantification (e.g., bootstrap intervals, quantile forests, or conformal prediction) will accompany point estimates, allowing decision-makers to prioritize buildings with both high vulnerability and high uncertainty for engineering inspection. Finally, active learning will guide the choice of the next buildings to analyze mechanically, focusing computational budget where it most reduces uncertainty. Operationally, deploying outputs into *QGIS* (vulnerability level + uncertainty overlays) will turn the **ML** layer from a computational accelerator into a practical, interpretable *decision support* tool for urban risk management.

8.6 Summary

This chapter presented a practical pipeline for fast, city-scale prediction of collapse coefficients (**CC**) once a carefully curated and representative training set is in place. We moved from an initial random split toward a clustering-based sampling strategy: *12* cluster-selected representatives were merged with *94* fully analyzed buildings, and the final labeled set comprised *106* samples. Model training and selection were conducted via *stratified 5-fold cross-validation* with all preprocessing performed within each fold to avoid leakage. We compared Linear Regression, Random Forest, and XGBoost; based on out-of-fold RMSE and R^2 , *XGBoost* showed a slight yet consistent advantage and was selected as the final model. The selected model was then refit on all 106 labeled samples and used to predict **CC** for the entire stock of *347* buildings, enabling subsequent mapping and analyses. The outlook points to integrating qualitative features and external field data, advancing explainability and uncertainty quantification, and leveraging active learning—toward robust, interpretable, and scalable urban decision support.

Chapter 9

Applications and Discussion

9.1 Urban-scale Applications and Decision-making

The proposed methodology enables the application of structural analysis results at the urban scale. By combining *virtual twins* (**VTs**) with the calculation of the *collapse coefficient* (**CC**) for each building, seismic vulnerability maps can be produced within a *geographic information systems* (**GIS**) environment. These maps not only provide an overview of the spatial distribution of seismic risk across the city but also translate complex numerical and *machine learning* (**ML**) outputs into intuitive visual layers. Through the use of color-coded classifications into four vulnerability levels, the results can be easily interpreted by municipal authorities and non-expert decision makers. This facilitates prioritization in retrofitting programs and resource allocation.

As established in Chapter 6, the four-level vulnerability framework and its statistical distribution enable consistent interpretation at the city scale. Building upon the **ML** predictions introduced in Chapter 8, the collapse coefficient can be extended across the building stock, making **GIS**-based mapping operational at scale. A representative four-level vulnerability map produced in *quantum geographic information system* (**QGIS**) was already presented in Fig. 4.3.

Moreover, due to its scalable nature, the framework can be adapted to other urban contexts. As demonstrated in European reference projects such as RISK-UE (Milutinovic & Trendafiloski, 2003) and the DaDO database (Project, 2022), an efficient methodology must ensure transferability and adaptability to heterogeneous urban datasets. The present approach preserves this flexibility by relying on information that is both accessible and easy to extract from maps and urban databases.

9.2 Supporting Emergency Management

One of the most relevant applications of the proposed methodology concerns its role in supporting emergency management before and after an earthquake. The classification of buildings into predefined vulnerability levels enables the rapid identification of critical areas within the urban fabric. This information can be directly exploited by civil protection agencies to plan preventive measures in advance and to prioritize interventions immediately after a seismic event.

The integration of vulnerability maps with additional geospatial data further enhances the usefulness of the tool in crisis scenarios. For example, by overlaying the classification of buildings with transportation networks, hospitals, or schools, decision makers can identify infrastructures at risk and determine which evacuation routes may be compromised. Such a rapid overview facilitates the allocation of rescue resources and the coordination of emergency operations.

The prioritization logic builds on the class distributions analyzed in Chapter 6, while the predictive layer stems from the supervised models presented in Chapter 8. The consistency of the methodology against macroseismic references was examined in Chapter 7.

Similar approaches have been implemented in European contexts, such as the EMS-98 framework (Grunthal, 1998) and the AEDES post-earthquake survey manual (della Protezione Civile, 2004), which provide standardized procedures for damage and usability assessment. The proposed framework advances these practices by introducing a scalable and semi-automated process that can deliver results in a significantly shorter time while remaining consistent with existing protocols.

9.3 Comparison with Existing Methods

To better contextualize the proposed framework, it is necessary to compare it with existing approaches for seismic vulnerability assessment. Traditional methods, such as the *rapid visual screening* (**RVS**) procedure (FEMA, 2015), are based on simplified checklists and field inspections. These approaches are widely used due to their simplicity and speed; however, their accuracy is limited and heavily dependent on the subjective judgment of the evaluator.

In contrast, macroseismic and mechanical models, such as those proposed by (Lagomarsino & Giovinazzi, 2006), provide a more detailed estimation of seismic performance. Nevertheless, these methods require relatively complete structural information and are difficult to implement efficiently at the urban scale. Similarly, European tools such as RISK-UE (Milutinovic & Trendafiloski, 2003) and the AEDES manual (della Protezione Civile, 2004) offer standardized frameworks for hazard analysis and post-earthquake assessment, but their large-scale application remains resource- and time-intensive.

As summarized in Table 9.1, the proposed framework balances data needs, accuracy, and scalability compared with **RVS** and macro-/mechanical models.

Table 9.1: Comparison of seismic vulnerability assessment approaches.

	RVS (e.g., FEMA)	Macroseismic / Mechanical Models	Proposed: VTs + ML
Required data	Visual checklists; limited structural info	Detailed structural/mechanical data	Basic urban data + VT database; scalable features
Time per building	Very low	High (analysis/modeling)	Low after training; batch inference
Accuracy/consistency	Variable; evaluator-dependent	High for modeled assets	High at scale; validated vs. macroseismic refs
Urban scalability	Yes (procedural)	No (resource-intensive)	Yes (GIS-ready; automated pipeline)
Automation potential	Moderate	Low	High (end-to-end: data → FE/EA → ML → GIS)
Output	Qualitative scores	Detailed performance metrics	4-level maps; CC prediction

This balance is evidenced by the agreement trends reported in Chapter 7 and by the urban-scale acceleration demonstrated in Chapter 8. The proposed methodology, by leveraging **VTs** and **ML**, aims to strike a balance between these two categories of methods. On the one hand, it retains the rigor of mechanical approaches through *finite element limit analysis* (**FELA**) and numerical modeling; on the other hand, it ensures the scalability and efficiency required for urban-scale applications. This dual advantage positions the framework as a bridge between traditional **RVS** methods and advanced computational tools.

9.4 Strengths and Innovations

The proposed methodology exhibits several key strengths that distinguish it from existing approaches.

First, its main advantage lies in **speed and efficiency**. By relying on a database generated from numerical simulations of **VTs** and subsequently processed through **ML** algorithms, the computational time is drastically reduced, allowing the analysis of hundreds of buildings at the urban scale. As shown in Chapter 8, the refined pipeline drastically reduces the computation time while preserving accuracy.

Second, the framework is characterized by **scalability and flexibility**. It is designed to adapt to the available data of any given city while remaining capable of being continuously updated and improved as new information becomes accessible, whether from field surveys or sensor-based monitoring.

Third, the methodology ensures **integration between mechanical modeling and ML**. Unlike purely statistical or purely mechanical approaches, this framework combines the benefits of both: It is grounded in the principles of the lower-bound theorem and numerical analysis, while also exploiting the predictive capacity and adaptability of data-driven models.

Fourth, the approach enhances **transparency and interpretability of results**. By employing explainable artificial intelligence (XAI) techniques, the model outputs can be presented in a user-friendly format suitable for non-expert decision makers. This feature, also emphasized in recent work by (Imani et al., 2025), increases the trustworthiness of the methodology for real-world applications.

Altogether, these features position the proposed framework as an **innovative, rapid, and user-oriented tool** for seismic vulnerability assessment.

9.5 Limitations and Challenges

Despite its notable strengths, the proposed methodology still faces several limitations and challenges.

First, there is a strong **dependence on data quality**. Although the framework relies on simple and easily accessible sources (e.g., urban maps or public databases), the accuracy of the results largely depends on the completeness and precision of such data. Any error or missing

information may lead to significant deviations in the outcomes.

Second, the **standardization of qualitative data** remains a critical challenge. Factors such as building age, maintenance status, or plan irregularities are often recorded in qualitative or subjective formats. Converting these descriptors into consistent numerical values suitable for computational processing is not straightforward.

Third, there is an inherent **gap between synthetic and real-world data**. The initial database is constructed from numerical models and **VTs**, which, while highly controllable, may not fully capture the complexity of actual buildings. For this reason, a progressive integration with field data, such as those available in the DaDO database (Project, 2022) or the EMS-98 framework (Grunthal, 1998), is required. Bridging this gap requires alignment with field evidence and macroseismic trends examined in Chapter 7, together with iterative dataset enrichment discussed in Chapter 8.

Fourth, the framework still requires **broader validation**. To increase reliability, the methodology must be tested and benchmarked under different scenarios and with diverse datasets.

The key limitations and corresponding mitigation paths are summarized in Table 9.2.

Table 9.2: Key limitations and mitigation paths.

Challenge	Description	Mitigation path
Data quality	Urban/GIS DBs may be incomplete; errors propagate.	Cleaning; cadastral checks; field audits.
Qualitative standardization	Age/maintenance/plan often textual.	Coding; ordinal→numeric; rater calibration.
Synthetic vs. real gap	VTs may miss real-world complexity.	Fuse field datasets (DaDO, EMS-98); iterative retrain.
Broader validation	Need tests across cities/scenarios.	Multi-city benchmarks; uncertainty; sensitivity.

Considering these limitations, the present approach should be seen as an important step forward, but one that still requires further development and testing before achieving full maturity.

9.6 Future Perspectives

The future development of the proposed methodology presents several promising directions, particularly in connection with modern technologies and real-time data integration.

First, the **integration with smart sensors and internet of things (IoT) technologies** represents a significant opportunity. The adoption of fiber optic sensors and structural health monitoring (SHM) systems—as highlighted in recent studies by (Minutolo et al., 2020), (H. Wang et al., 2023), and (Preethichandra, 2023)—enables the continuous collection of structural data. These datasets can be directly connected to **VT** models, allowing for real-time updates of vulnerability assessments.

Second, the framework shows strong potential for **rapid post-earthquake assessment**. In critical scenarios, the ability to quickly access reliable information on the vulnerability levels

of buildings is essential. By combining numerical analysis with **ML**, the proposed approach can serve as a foundation for real-time early warning and emergency management systems. Real-time updates can directly feed the mapping workflow summarized in Chapter 6 and the **ML**-based prediction services described in Chapter 8, enabling rapid post-earthquake screening.

Third, advances in **explainable artificial intelligence (XAI)** are expected to further strengthen the methodology. As demonstrated in Imani et al. (Imani et al., 2025), explainable **ML** frameworks increase the trustworthiness and acceptance of results by non-technical stakeholders and decision makers.

Fourth, the **promotion of interdisciplinary collaboration** is crucial. The integration of structural engineering, data science, and sensing technologies will pave the way for the development of user-friendly, accurate, and scalable tools. Such collaborations can transform the proposed framework into a comprehensive platform for urban risk management.

A compact view of the future directions and their expected impact is given in Table 9.3.

Table 9.3: Future directions and expected impact.

Direction	Opportunity	Expected impact
IoT/SHM integration	FO sensors; continuous streams $\rightarrow$ twins.	Near real-time updates; adaptive mapping.
Rapid post-EQ screening	ML + numerical priors for triage.	Faster routing & resource allocation.
Explainable AI (XAI)	Explanations for non-experts.	Higher trust; auditability.
Interdisciplinary collaboration	Structures + data sci. + sensing.	Usable, scalable urban-risk platform.

Overall, the future perspectives highlight that by combining real-world data, advanced algorithms, and innovative monitoring tools, the methodology can evolve into a system that is not only rapid and scalable, but also dynamic and adaptive.

9.7 Chapter Summary

This chapter discussed the potential applications and broader implications of the proposed framework. The methodology was shown to be useful at the urban scale, to support emergency management, and to provide a balanced alternative to both **RVS** and detailed mechanical models. Its strengths lie in efficiency, scalability, and transparency, while its limitations highlight the importance of data quality, standardization, and validation against real-world conditions. Finally, future perspectives suggest that integrating the framework with IoT-based monitoring, explainable AI, and interdisciplinary collaboration can transform it into a comprehensive tool for seismic risk management. These reflections connect the technical developments of Chapter 6, Chapter 7, and Chapter 8 with the overall conclusions presented in the final chapter. Overall, mechanics-to-map integration is aligned with (Zona et al., 2025), and the data-driven scaling leverages the approach in (Imani et al., 2025).

Chapter 10

Conclusions and Future Work

10.1 Summary of Findings

This thesis developed an integrated pipeline for urban-scale seismic vulnerability assessment of *reinforced concrete* (**RC**) buildings. The workflow starts from extracting geometric and descriptive data of buildings, proceeds with the construction of *virtual twin* (**VT**), and applies *finite element limit analysis* (**FELA**) to obtain the *collapse coefficient* (**CC**) for representative assets. Supervised *machine learning* (**ML**) models are then trained to extrapolate **CC** across the building stock, and the results are rendered as four-level, GIS-ready vulnerability maps. In doing so, the framework preserves mechanical grounding while achieving the speed and scale required for city-wide applications (Chapters 6 to 9).

10.2 Contributions

Scientific

- **Physics + data integration.** A cohesive formulation that couples lower-bound mechanics via **FELA** with supervised **ML** for urban inference, using **CC** as a quantitative response linking numerical analysis to mapping.
- **Urban-scale computational efficiency.** Significant reduction of analysis time through VT-based datasets and batch inference without abandoning the mechanical backbone.
- **Interpretable outputs.** Stability of the four-level classification against macroseismic trends and compatibility with explainable layers discussed in prior chapters.

Practical

- **Operational mapping.** Production of four-level vulnerability layers suitable for *geographic information systems* (**GIS**), updatable and transferable to other urban contexts.

- **Evidence-informed prioritization.** Use of a quantitative index (**CC**) to support pre-event planning (retrofitting programs) and post-event triage (rapid screening).

10.3 Limitations

- **Idealizations in VT models.** Representative geometries and simplified details inevitably omit certain real-world complexities (e.g., local defects, construction irregularities).
- **Field-data coverage and heterogeneity.** Uneven availability and quality of building information affects the reliability of **ML** extrapolation.
- **Standardizing qualitative descriptors.** Factors such as age, maintenance, and plan/height irregularities need clear and consistent encoding schemes so they can be used reliably in the computational process.
- **External validation breadth.** Wider cross-city testing and systematic reporting of uncertainty and sensitivity are still needed.
- **Resource constraints.** Data curation and on-site checks bound the achievable scale and cadence of updates.

10.4 Targeted Out-of-sample Validation

To independently verify the final model without re-labeling the entire test set, we conducted a targeted out-of-sample validation on **20 buildings** sampled across the prediction spectrum: five with the lowest predicted **CC**, ten near the median, and five with the highest predicted **CC**. For each case, the reference **CC** was obtained from the mechanical pipeline (**FELA** on **VT**) and standard regression metrics were computed.

On the 20 audited cases, the model achieved **MAE = 0.0136**, **RMSE = 0.0162**, and **MAPE = 1.14%**, confirming strong agreement with the mechanical baseline; *on the pooled audit set, the coefficient of determination was $R^2 = 0.982$* . Performance was consistent across the three strata (Table 10.1), and the parity plot (Figure 10.1) visually corroborates the low errors across both central and extreme regions of the distribution.

Table 10.1: Targeted 20-sample audit by prediction stratum (errors on **CC**).

Group	n	MAE	RMSE	MAPE (%)
LOW (lowest CC)	5	0.0147	0.0165	1.47
MID (near median)	10	0.0109	0.0132	0.87
HIGH (highest CC)	5	0.0178	0.0207	1.35
ALL	20	0.0136	0.0162	1.14

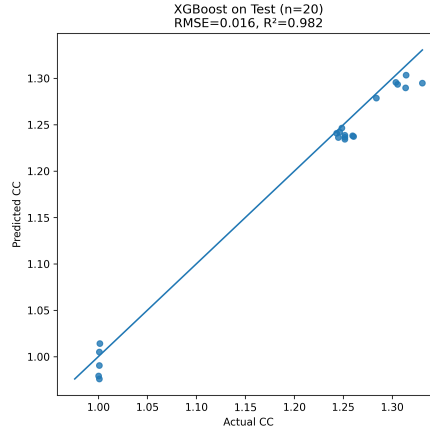


Figure 10.1: Parity plot of predicted vs. actual **CC** on the 20 audited buildings.

10.5 Future Work

1. **Integrating real-world data.** Systematic fusion with field repositories and remote-sensing products (including municipal databases and Copernicus EMS) to narrow the VT–reality gap and raise confidence in **CC** estimates.
2. **Enriching features with standardized qualitative data.** Robust coding schemes for age, maintenance, and irregularities; assessment of their marginal effects on **CC** and on the final class.
3. **Explainable AI (XAI).** Feature attributions and monotonicity constraints aligned with structural intuition (e.g., *ceteris paribus*, increasing number of stories should not increase **CC**).
4. **Expanded case studies.** Application to documented events (e.g., Zagreb 2020) with scenario analyses to assess transferability and calibrate thresholds.
5. **Multi-city validation and uncertainty.** Benchmarks across diverse urban fabrics; reporting confidence intervals for **CC** and sensitivity to key inputs.
6. **Towards an operational tool.** Packaging the pipeline into a **GIS**-centric application for routine use by stakeholders, with periodic VT database updates.

10.6 Closing Remarks

The proposed framework opens a practical route from mechanics-based analysis to actionable, city-scale decisions: **CC** derived via **FELA** is generalized by **ML** over the building stock and translated into four-level maps that non-experts can read. While limitations in data quality, qualitative standardization, and external validation remain, the evidence accumulated in this thesis indicates that combining **VT** and **ML**, anchored by **FELA**, can form a scientific, transparent, and scalable basis for rapid urban vulnerability assessment and its future operationalization.

As an external sanity check, a targeted 20-case audit across the prediction spectrum confirmed low errors (Table 10.1), reinforcing the practical viability of the proposed pipeline for city-scale screening.

Acknowledgments

I am deeply grateful to Prof. Renato Zona and Prof. Vincenzo Minutolo for their guidance and for our co-authored works that informed this thesis. I also thank Prof. Salvatore Losco, Prof. Henning Wessels, and the Data-Driven Modeling Group at TU Braunschweig for helpful discussions and a supportive research environment. I am indebted to my colleagues and friends for their feedback and encouragement throughout this work. Finally, my heartfelt thanks go to my family—my spouse and our sons—for their patience, sacrifices, and unwavering support during the long months of research and writing. This thesis would not have been possible without their love and understanding.

Appendix A: Useful Databases and Open-Source Resources for Seismic Hazard and Vulnerability Assessment

Overview: This appendix provides a list of useful databases and data resources for researchers in the field of seismic hazard, vulnerability, and risk assessment. These resources are mostly available as open-source platforms and are classified according to the type of data and intended use.

Open Data Appendix
1. EPOS — European Plate Observing System Address: https://www.epos-eu.org Data type: Seismic hazard and risk maps, analysis tools Description: Provides the latest European hazard and risk maps, with a focus on standardization across the continent.
2. EFEHR — European Facilities for Earthquake Hazard and Risk Address: http://www.efehr.org Data type: Hazard, vulnerability, exposure maps; <i>geographic information systems</i> (GIS) outputs Description: Host platform for ESHM20 (European Seismic Hazard Model) and ESRM20 (European Seismic Risk Model).
3. GEM — Global Earthquake Model Address: https://www.globalquakemodel.org Data type: Fragility models, exposure data, risk tools Description: International reference for structural and statistical models, covering various regions including Europe.
4. GFZ — Helmholtz Centre Potsdam Address: https://www.gfz-potsdam.de Data type: Hazard assessment, earthquake monitoring, urban risk analysis Description: Analytical platforms to improve seismic preparedness and response in Europe.
5. Eurocode Resources — European Commission Address: https://eurocodes.jrc.ec.europa.eu Data type: Seismic design codes (EN 1998), guidelines, sample files Description: Includes the second generation of Eurocode 8 and explanatory papers on application.
6. EVR Platform — Romania

Address: <https://evr.mdipa.ro/en/>

Data type: *rapid visual screening* (**RVS**) platform

Description: Online tool for recording and classifying at-risk buildings in Romania.

7. NCSEA — 18th World Conference on Earthquake Engineering (WCEE 2024)

Address: <https://www.ncsea.com/news-post/insights-from-the-18th-world-conference-on-earthquake-engineering-wcee-2024>

Data type: Summary of global earthquake engineering conference findings

Description: Introduces new approaches to monitoring, **RVS**, and the use of digital tools for vulnerability assessment.

Appendix B: Complete Dataset of Analyzed Structural Models

Notes: This table contains the numerical models *virtual twins* (VTs) used in the *machine learning* (ML) process. For each model, the input parameters include the geometric characteristics, and the intermediate and final outputs from the structural limit analysis are listed at the end of the table. The meaning of each parameter is given in Table 4.

Table 3: Complete dataset of 106 analysed structural models.

Model	n_x	n_y	n_z	l_x	l_z	PE	SE_x	SE_z	PC	SC_x	SC_z	CC
Telaio_5_5_3_8_5	5	5	3	8.00	5.00	2,133.88	925.95	141.15	2,463.48	1,231.01	320.91	1.329,5
Telaio_7_5_2_4_6_5_5	7	5	2	4.60	5.50	1,648.80	759.90	140.48	1,776.03	823.31	308.27	1.083,4
Telaio_2_7_7_7_5	2	7	7	7.00	5.00	1,843.43	666.34	86.16	1,866.64	864.31	86.17	1.000,1
Telaio_4_5_8_4_4	4	5	8	4.00	4.00	1,416.76	554.77	148.26	1,557.76	600.71	148.28	1.000,1
Telaio_10_5_4_5_4	10	5	4	5.00	4.00	1,801.76	916.30	137.30	1,926.43	990.64	292.50	1.081,1
Telaio_8_4_3_6_7	8	4	3	6.00	7.00	2,188.69	1,233.03	205.34	2,251.94	1,537.24	489.42	1.246,7
Telaio_8_2_2_5_4_5	8	2	2	5.00	4.50	1,783.46	2,640.90	678.77	1,832.44	3,100.61	1,656.03	1.174,1
Telaio_7_3_5_5_5_5	7	3	5	5.50	5.00	2,001.79	1,690.72	341.93	2,045.82	2,053.25	689.36	1.214,4
Telaio_10_1_6_5_5	10	1	6	5.00	5.00	1,744.20	5,432.99	2,031.64	1,798.29	6,041.10	2,031.69	1.000,0
Telaio_9_2_4_4_5	9	2	4	4.00	5.00	1,436.26	1,725.54	678.92	1,553.17	2,055.07	1,664.49	1.191,0
Telaio_11_2_7_5_4	11	2	7	5.00	4.00	1,774.57	2,629.36	679.89	1,923.28	3,086.29	1,656.44	1.173,8
Telaio_9_2_4_6_5_5	9	2	4	6.00	5.50	2,114.07	2,571.86	679.72	2,302.29	3,094.00	1,651.17	1.203,0
Telaio_5_2_4_8_5_5_5	5	2	4	8.50	5.50	2,109.34	2,464.26	679.44	2,457.96	3,133.73	691.01	1.017,0
Telaio_3_5_4_6_6	3	5	4	6.00	6.00	218.46	97.83	15.16	231.23	123.41	15.17	1.001,0
Telaio_5_5_3_5_4_5	5	5	3	5.00	4.50	1,802.85	907.41	144.10	1,944.47	973.42	310.34	1.072,8
Telaio_8_4_4_4_4	8	4	4	4.00	4.00	1,423.10	723.43	207.76	1,550.12	821.12	471.29	1.135,0
Telaio_8_5_6_5_6	8	5	6	5.00	6.00	1,802.10	913.94	138.73	1,931.62	986.31	292.39	1.079,2
Telaio_5_5_3_5_4_5	5	5	3	5.40	5.00	1,955.97	994.64	143.66	2,083.20	1,147.79	311.81	1.154,0
Telaio_7_4_7_4_7_3_6	7	4	7	4.70	3.60	1,692.18	1,028.61	208.51	1,851.84	1,153.84	208.52	1.000,1
Telaio_8_6_3_5_1_5_3	8	6	3	5.10	5.30	1,835.84	779.00	99.76	2,007.09	821.33	218.58	1.054,3
Telaio_12_3_5_5_5	12	3	5	5.00	5.00	1,810.52	1,673.52	339.85	1,853.55	1,945.99	734.01	1.162,8
Telaio_9_6_3_3_6_5	9	6	3	3.60	5.00	1,127.36	366.67	100.12	1,251.37	396.35	214.58	1.081,0
Telaio_7_4_4_4_7_4	7	4	4	4.70	4.00	1,692.18	1,028.61	208.51	1,851.84	1,153.84	477.47	1.121,7
Telaio_6_6_4_4_5	6	6	4	4.00	5.00	1,318.74	456.99	102.65	1,572.00	487.84	215.95	1.067,5
Telaio_5_5_3_5_6	5	5	3	5.00	6.00	1,802.85	907.41	144.10	1,944.47	973.42	310.34	1.072,8
Telaio_9_5_3_4_2_4_4	9	5	3	4.20	4.40	1,494.58	625.13	138.69	1,592.06	683.11	306.86	1.092,7
Telaio_9_5_3_4_4_2	9	5	3	4.00	4.20	1,417.69	562.30	138.88	1,496.40	616.50	305.78	1.096,4
Telaio_9_7_3_4_6	9	7	3	4.00	6.00	1,239.96	389.33	75.25	1,378.35	411.74	159.73	1.057,6
Telaio_11_5_2_6_9_5_5	11	5	2	6.90	5.50	2,278.85	951.11	136.31	2,598.00	1,225.59	319.02	1.288,6
Telaio_10_7_2_6_2_8	10	7	2	6.20	8.00	1,907.00	686.06	73.94	2,414.16	874.93	165.10	1.275,3
Telaio_8_7_4_6_75_5	8	7	4	6.75	5.00	1,856.51	675.64	74.61	2,612.31	875.38	156.24	1.295,6
Telaio_6_5_2_7_6	6	5	2	7.00	6.00	2,274.84	950.33	139.55	2,652.18	1,229.99	292.69	1.294,3
Telaio_6_6_2_5_6	6	6	2	5.00	6.00	1,798.00	742.52	101.93	1,968.12	781.25	218.39	1.052,2
Telaio_6_6_2_6_6	6	6	2	6.00	6.00	2,156.98	809.05	101.24	2,324.48	1,023.19	220.86	1.264,7
Telaio_7_7_4_5_5	7	7	4	5.00	5.00	1,747.39	629.03	76.07	1,847.48	653.46	161.86	1.038,8
Telaio_13_5_2_7_5_5	13	5	2	7.00	5.50	2,261.76	947.66	136.09	2,630.94	1,223.67	319.42	1.291,2
Telaio_6_5_5_6_5_5_3	6	5	5	6.50	5.30	2,353.23	963.28	139.98	2,469.85	1,229.47	212.41	1.276,3
Telaio_10_4_2_6_7_5_5	10	4	2	6.70	5.50	2,427.59	1,208.00	204.13	2,502.73	1,535.60	494.83	1.271,2
Telaio_10_6_3_5_7_6	10	6	3	5.70	6.00	2,065.46	816.50	98.31	2,205.11	1,021.60	220.74	1.251,2
Telaio_10_5_2_5_7_7	10	5	2	5.70	7.00	2,069.86	985.60	136.91	2,169.69	1,226.93	292.75	1.244,9
Telaio_9_6_2_5_7	9	6	2	5.00	7.00	1,797.27	747.14	99.21	1,922.61	789.57	219.60	1.056,8

Continued on next page

Model	n_x	n_y	n_z	l_x	l_z	PE	SE_x	SE_z	PC	SC_x	SC_z	CC
Telaio_6_6_3_6_5.7	6	6	3	6.00	5.70	2,156.98	809.05	101.24	2,324.48	1,023.19	220.86	1.264,7
Telaio_3_4_3_6_6.1	3	4	3	6.00	6.10	2,188.19	1,238.48	224.93	2,352.00	1,548.19	224.94	1.000,1
Telaio_4_5_2_6.15_6.75	4	5	2	6.15	6.75	2,242.40	973.20	145.77	2,356.54	1,231.71	317.45	1.265,6
Telaio_6_6_2_6.8_6.65	6	6	2	6.80	6.65	2,057.82	790.59	100.74	2,608.04	1,023.63	222.78	1.294,8
Telaio_8_3_2_7_6.2	8	3	2	7.00	6.20	2,498.18	1,628.50	339.85	2,599.39	2,055.25	727.08	1.262,1
Telaio_4_4_2_5.9_6.25	4	4	2	5.90	6.25	2,151.35	1,238.57	216.05	2,234.57	1,545.09	484.98	1.247,5
Telaio_11_5_3_6.5_4.9	11	5	3	6.50	4.90	2,341.47	961.96	136.39	2,453.01	1,225.95	320.71	1.274,4
Telaio_5_5_3_6.6_4.9	5	5	3	6.60	4.90	2,342.67	960.56	142.41	2,512.33	1,229.31	316.16	1.279,8
Telaio_4_6_3_6.4_5.4	4	6	3	6.40	5.40	2,117.53	799.24	104.97	2,441.44	1,024.79	223.36	1.282,2
Telaio_4_3_3_4_5.45	4	3	3	4.00	5.45	1,429.67	1,012.04	361.20	1,518.99	1,197.97	742.61	1.183,7
Telaio_6_7_4_6.35_6.3	6	7	4	6.35	6.30	1,899.85	683.29	76.31	2,483.23	876.42	156.94	1.282,7
Telaio_7_9_2_6.35_6.75	7	9	2	6.35	6.75	1,574.97	528.90	47.43	2,255.47	681.54	100.35	1.288,6
Telaio_2_5_4_6.5_5.9	2	5	4	6.50	5.90	2,380.64	962.60	159.17	2,416.88	1,230.87	159.19	1.000,1
Telaio_4_6_2_5.65_4.15	4	6	2	5.65	4.15	2,047.57	817.64	105.47	2,212.90	998.45	222.17	1.221,1
Telaio_4_4_2_6.8_4.7	4	4	2	6.80	4.70	2,492.67	1,208.70	214.27	2,566.97	1,546.03	491.48	1.279,1
Telaio_5_4_3_6.1_6.5	5	4	3	6.10	6.50	222.71	122.94	21.15	239.24	154.14	48.74	1.253,7
Telaio_6_5_2_5.85_6.3	6	5	2	5.85	6.30	2,127.67	981.19	140.60	2,236.44	1,228.98	293.06	1.252,5
Telaio_4_4_2_6.65_6.65	4	4	2	6.65	6.65	2,435.92	1,213.48	214.55	2,511.12	1,545.84	490.41	1.273,9
Telaio_7_5_3_6.55_4.9	7	5	3	6.55	4.90	2,341.37	962.26	138.74	2,483.08	1,228.92	319.87	1.277,1
Telaio_6_5_3_6.75_5.75	6	5	3	6.75	5.75	2,313.61	956.72	139.76	2,560.75	1,229.62	317.05	1.285,2
Telaio_4_3_3_6.25_5.4	4	3	3	6.25	5.40	2,280.63	1,665.11	351.43	2,338.76	2,066.94	718.69	1.241,3
Telaio_7_6_4_6.1_6.1	7	6	4	6.10	6.10	2,141.11	807.03	100.14	2,410.11	1,022.88	222.52	1.267,5
Telaio_4_3_2_5.5_6.9	4	3	2	5.50	6.90	2,002.63	1,698.10	354.26	2,059.57	2,066.15	734.02	1.216,7
Telaio_4_3_2_5.5_6.9	4	3	2	5.50	6.90	2,002.63	1,698.10	354.26	2,059.57	2,066.15	734.02	1.216,7
Telaio_4_3_2_5.5_6.9	4	3	2	5.50	6.90	2,002.63	1,698.10	354.26	2,059.57	2,066.15	734.02	1.216,7
Telaio_6_5_5_7.1_5.8	6	5	5	7.10	5.80	2,259.58	947.82	139.47	2,507.44	1,229.85	211.53	1.297,6
Telaio_4_3_3_6_6	4	3	3	6.00	6.00	2,192.56	1,675.80	352.32	2,245.23	2,066.51	721.10	1.233,1
Telaio_8_5_4_5_5	8	5	4	5.00	5.00	1,802.10	913.94	138.73	1,931.62	986.31	292.39	1.079,2
Telaio_9_3_2_5.9_3.5	9	3	2	5.90	3.50	2,128.24	1,672.73	339.96	2,186.96	2,051.95	826.07	1.226,7
Telaio_10_5_2_6.9_3.5	10	5	2	6.90	3.50	2,280.10	951.54	136.49	2,600.26	1,226.40	292.75	1.288,9
Telaio_10_4_2_5.7_3.5	10	4	2	5.70	3.50	2,074.17	1,242.79	204.39	2,138.29	1,536.59	487.63	1.236,4
Telaio_10_4_2_7.4_3.5	10	4	2	7.40	3.50	2,407.72	1,185.70	204.06	2,762.05	1,534.84	499.35	1.294,5
Telaio_10_5_2_6_3	10	5	2	6.00	3.00	2,184.42	976.68	136.78	2,275.93	1,226.77	292.79	1.256,1
Telaio_11_3_2_7_3.5	11	3	2	7.00	3.50	2,484.91	1,623.22	340.13	2,591.35	2,049.14	836.99	1.262,4
Telaio_10_5_2_7.1_3.5	10	5	2	7.10	3.50	2,249.59	946.25	136.44	2,673.28	1,226.34	292.70	1.296,0
Telaio_8_3_1_8_5	8	3	1	8.00	5.00	225.25	158.89	33.97	297.67	205.45	84.55	1.293,0
Telaio_10_4_2_6.1_3	10	4	2	6.10	3.00	2,226.57	1,228.43	204.26	2,283.06	1,536.36	484.41	1.250,7
Telaio_13_4_2_7_4	13	4	2	7.00	4.00	2,515.40	1,196.38	204.07	2,717.36	1,531.35	496.83	1.280,0
Telaio_5_4_4_5_4	5	4	4	5.00	4.00	1,807.60	1,173.86	213.69	1,965.01	1,305.80	362.28	1.112,4
Telaio_4_9_3_6_5.1	4	9	3	6.00	5.10	1,604.26	533.72	49.80	1,983.25	681.64	100.15	1.277,2
Telaio_5_9_3_6_5.8	5	9	3	6.00	5.80	1,600.77	534.19	48.82	2,205.50	681.12	101.09	1.275,1
Telaio_4_3_4_6_5_4	4	3	4	6.50	4.00	2,364.87	1,654.70	350.59	2,432.69	2,062.61	350.61	1.000,1
Telaio_4_5_3_6_5_5.7	4	5	3	6.50	5.70	2,366.21	963.54	145.37	2,483.37	1,231.98	296.54	1.278,6
Telaio_6_4_2_6.7_6.25	6	4	2	6.70	6.25	2,451.55	1,210.34	207.37	2,516.91	1,540.10	493.30	1.272,5
Telaio_5_6_2_7_6.6	5	6	2	7.00	6.60	2,038.15	785.84	102.46	2,760.87	1,024.66	224.66	1.303,9
Telaio_3_6_3_6.3_5.75	3	6	3	6.30	5.75	2,137.77	802.30	108.99	2,170.60	1,026.38	109.00	1.000,1
Telaio_12_5_3_7_4	12	5	3	7.00	4.00	2,262.56	947.92	136.13	2,632.55	1,224.32	292.83	1.291,6
Telaio_7_6_2_7_6.75	7	6	2	7.00	6.75	2,030.48	786.73	99.66	2,762.45	1,023.46	225.09	1.300,9
Telaio_6_7_3_6.45_5	6	7	3	6.45	5.00	1,890.15	681.26	76.27	2,517.97	876.44	156.93	1.286,5
Telaio_6_8_4_7_5.55	6	8	4	7.00	5.55	1,674.19	584.60	59.50	2,245.14	766.82	127.67	1.311,7
Telaio_4_4_3_5.5_5.65	4	4	3	5.50	5.65	1,999.02	1,252.83	216.90	2,089.26	1,544.85	374.51	1.233,1
Telaio_4_7_3_7_7	4	7	3	7.00	7.00	184.61	66.88	7.89	207.97	87.76	15.19	1.312,3
Telaio_4_4_2_5.5_4.75	4	4	2	5.50	4.75	199.90	125.19	21.67	208.93	154.48	48.20	1.234,0
Telaio_7_5_2_6.4_6.8	7	5	2	6.40	6.80	233.71	96.54	13.87	242.88	123.00	31.62	1.274,1
Telaio_5_7_2_6.2_6.2	5	7	2	6.20	6.20	191.81	68.51	7.76	240.31	87.60	16.46	1.278,6
Telaio_5_5_3_5_5.3	5	5	3	5.00	5.30	180.29	90.64	14.40	194.45	97.34	31.03	1.074,0
Telaio_5_7_3_6.4_5.3	5	7	3	6.40	5.30	189.87	68.10	7.76	249.58	87.60	16.49	1.286,4

Continued on next page

Model	n_x	n_y	n_z	l_x	l_z	PE	SE_x	SE_z	PC	SC_x	SC_z	CC
Telaio_6_2_3_6.8_6.15	6	2	3	6.80	6.15	240.34	254.20	67.84	251.28	311.88	164.77	1.226,9
Telaio_4_4_2_5.9_6.25	4	4	2	5.90	6.25	2,151.35	1,238.57	216.05	2,234.57	1,545.09	484.98	1.247,5
Telaio_4_3_2_6.5_6.44	4	3	2	6.50	6.44	236.49	165.38	35.04	243.27	206.79	72.92	1.250,4
Telaio_10_6_3_6.9_5.85	10	6	3	6.90	5.85	203.72	78.67	9.78	262.75	102.11	22.39	1.297,9
Telaio_4_4_2_5_6.5	4	4	2	5.00	6.50	180.81	116.82	21.78	191.04	129.57	47.83	1.109,1
Telaio_4_2_2_5.5_4.2	4	2	2	5.50	4.20	197.81	263.25	68.79	203.45	313.73	165.27	1.191,7
Telaio_6_4_5_6_6.3	6	4	5	6.00	6.30	218.89	123.22	20.81	225.97	153.91	35.14	1.249,1
Telaio_20_3_3_6_5.6	20	3	3	6.00	5.60	214.06	165.88	34.00	221.18	204.04	82.71	1.230,0

Feature Description: This table contains the numerical models **VTs** used in the **ML** process. For each model, the input parameters include the geometric characteristics, and the intermediate and final outputs from the structural limit analysis are listed at the end of the table. The meaning of each parameter is given in Table 4.

Table 4: Description of each parameter used in the dataset

Feature	Unit	Description
nx	–	Number of pillars in x direction (plan)
ny	–	Number of pillars in y direction (out of plane) or number of floors
nz	–	Number of pillars in z direction (plan)
lx	m	Span length in x direction
lz	m	Span length in z direction
PE	–	Elastic self weight multiplier
SE _x	–	Elastic seismic x multiplier
SE _z	–	Elastic seismic z multiplier
PC	–	Plastic self weight multiplier
SC _x	–	Plastic seismic x multiplier
SC _z	–	Plastic seismic z multiplier
CC	–	Collapse Coefficient

Bibliography

- Aljaafreh, A., Alzubi, Y., Al-Kharabsheh, E., & Yasin, B. (2023). Seismic performance of reinforced concrete structures with concrete deficiency caused by in-situ quality management issues. *Civil Engineering Journal*, 9(8), 1957–1970. <https://doi.org/10.28991/CEJ-2023-09-08-010>
- Bahmanoo, S. (2021, August 31). BIM-based seismic loss assessment for instrumented buildings [Masters thesis]. Concordia University. <https://spectrum.library.concordia.ca/id/eprint/988984/>
- Bal, I., Gulay, F., & Tezcan, S. (2008). A new approach for the preliminary seismic assessment of rc buildings: P25 scoring method. *The 14th World Conference on Earthquake Engineering*, 14 WCEE.
- Baldassarre, B., Conticelli, E., & Santangelo, A. (2024). Planning for more resilient and safer cities: A new methodology for seismic risk assessment at the urban scale, applied to a case study in Italy. *Sustainability*, 16(5), 1892. <https://doi.org/10.3390/su16051892>
- Bathe, K.-J. (2006). Finite element procedures. Klaus-Jurgen Bathe.
- Belytschko, T., Liu, W. K., Moran, B., & Elkhodary, K. (2014). Nonlinear finite elements for continua and structures. John Wiley & Sons.
- Benedetti, D., & Petrini, V. (1984). Sulla vulnerabilità sismica di edifici in muratura: Un metodo di valutazione. a method for evaluating the seismic vulnerability of masonry buildings. *L'industria delle Costruzioni*, (149), 66–74.
- Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic construction digital twin: Directions for future research. *Automation in construction*, 114, 103179.
- Borzi, B., Pinho, R., & Crowley, H. (2008). Simplified pushover-based vulnerability analysis for large-scale assessment of rc buildings. *Engineering structures*, 30(3), 804–820.
- Braga, F., Dolce, M., Liberatore, D., et al. (1982). A statistical study on damaged buildings and an ensuing review of the msk-76 scale. *7th European Conference on Earthquake Engineering*, 7, 431–450.
- Calvi, G. M., Pinho, R., Magenes, G., Bommer, J. J., Restrepo-Vélez, L. F., & Crowley, H. (2006). Development of seismic vulnerability assessment methodologies over the past 30 years. *ISET Journal of Earthquake Technology*, 43(3), 75–104. <https://home.iitk.ac.in/~vinaykg/Iset472.pdf>
- Chan, A. H., Pastor, M., Schrefler, B. A., Shiomi, T., & Zienkiewicz, O. C. (2022). Computational geomechanics: Theory and applications. John Wiley & Sons.

- Chen, W. F., & Han, D. J. (1988). Plasticity for structural engineers. Springer-Verlag.
- Chen, W.-F., Han, D.-J., & Han, D.-J. (2007). Plasticity for structural engineers. J. Ross publishing.
- Chopra, A. K., & Goel, R. K. (2002). A modal pushover analysis procedure for estimating seismic demands for buildings. *Earthquake engineering & structural dynamics*, 31(3), 561–582.
- Civil Protection Department. (n.d.). Seismic classification. <https://rischi.protezionecivile.it/en/seismic/activities/emergency-planning-and-damage-scenarios/seismic-classification/> Presidency of the Council of Ministers, Italy. Retrieved June 19, 2025.
- Coburn, A., & Spence, R. (2002). Earthquake protection. John Wiley & Sons.
- Cook, R. D., Malkus, D. S., Plesha, M. E., & Witt, R. J. (2007). Concepts and applications of finite element analysis.
- Crowley, H., Despotaki, V., Rodrigues, D., Silva, V., Toma-Danila, D., Riga, E., Karatzetzou, A., Fotopoulou, S., Zugic, Z., Sousa, L., Ozcebe, S., & Gamba, P. (2020). Exposure model for european seismic risk assessment. *Earthquake Spectra*, 36(1), 252–273. <https://doi.org/10.1177/8755293020919429>
- della Protezione Civile, D. (2004). Manuale per la compilazione della scheda di rilevamento del danno, pronto intervento e agibilità per edifici ordinari nell'emergenza post-sismica (AEDES). Presidenza del Consiglio dei Ministri, Italia.
- Demetriou, D., Polydorou, T., Nicolaides, D., & Petrou, M. F. (2024). A clustering machine learning approach for improving concrete compressive strength prediction. *Engineering Reports*, 6(11), e12934. <https://doi.org/10.1002/eng2.12934>
- Dimovska, S. (2023). Methodology for seismic vulnerability assessment of existing masonry buildings in urban centres. application to the eixample district in barcelona [Doctoral dissertation, Universitat Politècnica de Catalunya].
- Dolce, M., Kappos, A., Masi, A., Penelis, G., & Vona, M. (2006). Vulnerability assessment and earthquake damage scenarios of the building stock of potenza (southern italy) using italian and greek methodologies. *Engineering Structures*, 28(3), 357–371. <https://doi.org/10.1016/j.engstruct.2005.08.009>
- Dolce, M., & Ponzio, F. (2002). Non-linear seismic response of ecs designed rc building structures. *Journal of Earthquake Engineering*, 6, 357–373. <https://doi.org/10.1080/13632460209350421>
- Dolce, M., Prota, A., Borzi, B., da Porto, F., Lagomarsino, S., Magenes, G., Moroni, C., Penna, A., Polese, M., Speranza, E., et al. (2021). Seismic risk assessment of residential buildings in italy. *Bulletin of Earthquake Engineering*, 19, 2999–3032.
- Drucker, D. C. (1959). A definition of stable inelastic material. *Journal of Applied Mechanics*, 26(1), 101–106. <https://doi.org/10.1115/1.4011929>
- Drucker, D. C., & Prager, W. (1952). Soil mechanics and plastic analysis or limit design. *Quarterly of applied mathematics*, 10(2), 157–165.

- Elez, J., Silva, P. G., Pérez-López, R., Giner-Robles, J. L., Rodríguez-Pascua, M. A., & Sánchez-Sánchez, Y. (2025). Estimating the potential consequences of historical spanish earthquakes today: PAGER risk scenarios for seismic emergency management in spain. *Natural Hazards*, 121(10), 11489–11521. <https://doi.org/10.1007/s11069-025-07250-y>
- Elyasi, N., Kim, E., & Yeum, C. M. (2024). A machine-learning-based seismic vulnerability assessment approach for low-rise rc buildings. *Journal of Earthquake Engineering*, 28(3), 760–776.
- FEMA. (2023). Hazus estimated annualized earthquake losses for the united states (tech. rep.). Federal Emergency Management Agency (US). Washington, D.C.
- FEMA. (2015). Rapid visual screening of buildings for potential seismic hazards: A handbook. Federal Emergency Management Agency. <https://www.fema.gov/emergency-managers/risk-management/earthquake/training/fema-p-154>
- FEMA. (2017). Rapid visual screening of buildings for potential seismic hazards: A handbook (tech. rep.). Federal Emergency Management Agency (US). Redwood City, California.
- Ferranti, G., Greco, A., Pluchino, A., Rapisarda, A., & Scibilia, A. (2024). Seismic vulnerability assessment at an urban scale by means of machine learning techniques. *Buildings*, 14(2), 309.
- Ferreira, T. (2010). Assessment of seismic vulnerability of old urban nuclei: Application to the old urban nucleus of seixal [Doctoral dissertation, Faculty of Engineering of the University of Porto].
- Ferreira, T., Rodrigues, H., & Vicente, R. (2020). Seismic vulnerability assessment of existing reinforced concrete buildings in urban centers. *Sustainability*, 12(5). <https://doi.org/10.3390/su12051996>
- Filippou, C. A., Votsis, R., Tantele, E., Marangos, O., Fotiou, K., & Kyriakides, N. (2024). *geographic information systems (GIS)-based seismic risk and loss estimation platform for cyprus* [Backup Publisher: International Society for Optics and Photonics]. In A. Christofe, S. C. Michaelides, D. G. Hadjimitsis, C. Danezis, K. Themistocleous, N. Kyriakides, & G. Schreier (Eds.), *Tenth international conference on remote sensing and geoinformation of the environment (RSCy2024)* (p. 1321219, Vol. 13212). SPIE. <https://doi.org/10.1117/12.3037318>
- Foulser-Piggott, R., Spence, R., Eguchi, R., & King, A. (2016). Using remote sensing for building damage assessment: GEOCAN study and validation for 2011 christchurch earthquake. *Earthquake Spectra*, 32(1), 611–631. <https://doi.org/10.1193/051214EQS067M>
- Frascadore, R., Ludovico, M. D., Prota, A., G. Verderame, M. G., Manfredi, G., Dolce, M., & Cosenza, E. (2015). Local strengthening of reinforced concrete structures as a strategy for seismic risk mitigation at regional scale. *Earthquake Spectra*, 31(2), 1083–1102. <https://doi.org/10.1193/122912EQS361M>
- Giovinazzi, S., & Lagomarsino, S. (2004). A macroseismic method for the vulnerability assessment of buildings. *13th World Conference on Earthquake Engineering*, 896, 1–6.

- GNDT-SSN. (1994). Exposure and vulnerability and first and second level damage detection sheet (walled and reinforced concrete) (tech. rep.). National Group for Earthquake Defense. Rome, Italy.
- Google. (n.d.). Google maps [Online mapping service]. Retrieved August 12, 2025, from <https://maps.google.com>
- Greenberg, H. (1949). Complementary minimum principles for an elastic-plastic material. *Quarterly of Applied Mathematics*, 7(1).
- Grunthal, G. (1998). European macroseismic scale 1998. European Seismological Commission.
- Hidayat, B. A., Hu, H.-T., Hsiao, F.-P., Han, A. L., Pita, P., & Haryanto, Y. (2020). Seismic performance of non-ductile detailing RC frames: An experimental investigation. *Earthquakes and Structures*, 19(6), 485–498. <https://doi.org/10.12989/EAS.2020.19.6.485>
- Hill, R. (1998). The mathematical theory of plasticity (Vol. 11). Oxford University Press.
- Hirosawa, M., Sugano, S., & Kaminosono, T. (1992). Seismic evaluation method and restoration techniques for existing and damaged buildings developed in japan. In *Retrofitting and restration of buildings in japan* (pp. 1–69). Retrofitting; restration of buildings in Japan.
- Hughes, T. J. (2003). The finite element method: Linear static and dynamic finite element analysis. Courier Corporation.
- Ilyushin, A. (1963). Plasticity: Fundamentals of general mathematical theory. Academy of Sciences, USSR.
- Ilyushin, A. (1948). The theory of elasto-plastic strains and its application. *Bulletin of Academic Science, URSS, Sec. Tech. Services*, 769–788.
- Imani, H., Zona, R., Arcieri, A., Di Bonito, L. P., Palladino, S., & Minutolo, V. (2025). eXplainable artificial intelligence framework for structure’s limit load estimation. *Proceedings of the 10th International Conference on Internet of Things, Big Data and Security (IoTBDs 2025)*. <https://doi.org/10.5220/0013519800003944>
- IMIT. (2017, February). Allegato a: Linee guida per la classificazione del rischio sismico delle costruzioni [in Italian].
- Infrastructures, M. (2020). Allegato a linee guida per la classificazione del rischio sismico delle costruzioni [Retrieved from www.mit.gov.it].
- Ioan Cuza, A. (2021). Overview of the seismic vulnerability problem of the urban settlements in romania. *Geopatterns*, 6(1). <https://doi.org/10.5719/GeoP.6/3>
- Jimenez, J. C., & Dela Cruz, O. G. (2024). Machine learning for seismic vulnerability assessment: A review [Series Title: Lecture Notes in Civil Engineering]. In T. Liu & E. Liu (Eds.), *Proceedings of the 2nd international conference on advanced civil engineering and smart structures* (pp. 177–187, Vol. 474). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-1514-5_19
- Kappos, A. J., Panagopoulos, G., & Penelis, G. G. (2006). A hybrid method for the vulnerability assessment of r/c and URM buildings [Publisher: Springer]. *Bulletin of Earthquake Engineering*, 4, 391–413. <https://doi.org/10.1007/s10518-006-9023-0>

- Karampinis, I., Iliadis, L., & Karabinis, A. (2024). Rapid visual screening feature importance for seismic vulnerability ranking via machine learning and SHAP values. *Applied Sciences*, 14(6), 2609. <https://doi.org/10.3390/app14062609>
- Lagamarsino, S., Cattari, S., & Ottonelli, D. (2021). The heuristic vulnerability model: Fragility curves for masonry buildings. *Bulletin of Earthquake Engineering*, 19(8), 3129–3163. <https://doi.org/10.1007/s10518-021-01063-7>
- Lagamarsino, S., & Giovinazzi, S. (2006). Macroseismic and mechanical models for the vulnerability and damage assessment of current buildings. *Bulletin of Earthquake Engineering*, 4(4), 415–443. <https://doi.org/10.1007/s10518-006-9024-z>
- Leggieri, V., Mastrodonato, G., & Uva, G. (2022). GIS multisource data for the seismic vulnerability assessment of buildings at the urban scale. *Buildings*, 12(5), 523. <https://doi.org/10.3390/buildings12050523>
- Lopes, G. C., Silva, V., Costa, C., Vicente, R., & Oliveira, C. S. (2024). Advancing the understanding of earthquake risk in portugal. *Bulletin of Earthquake Engineering*, 22(11), 5379–5401. <https://doi.org/10.1007/s10518-024-01975-0>
- Losco, S., & Macchia, L. (2016). La vulnerabilità sismica della nuova conza della campania [Planum].
- Losco, S., Macchia, L., & Marino, P. (2012). Vulnerabilità sismica metodi a confronto: Il caso di bisaccia (av). *Planum*, 2.
- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30.
- Maier, G. (1969). Complementary plastic work theorems in piecewise-linear elastoplasticity. *International Journal of Solids and Structures*, 5(3), 261–270. [https://doi.org/10.1016/0020-7683\(69\)90063-8](https://doi.org/10.1016/0020-7683(69)90063-8)
- Manea, E. F., Danciu, L., Cioflan, C. O., Toma-Danila, D., & Gerstenberger, M. C. (2025). Testing the 2020 european seismic hazard model (ESHM20) against observations from romania. *Natural Hazards and Earth System Sciences*, 25(1), 1–12. <https://doi.org/10.5194/nhess-25-1-2025>
- Marzani, G., Cavalieri, B., Santangelo, A., Triller, P., Kreslin, M., Fassoulas, C., & Tondelli, S. (2025). Reducing seismic vulnerability of historic areas: Moving from good practices to tailored roadmaps. *Sustainability*, 17(11), 5062. <https://doi.org/10.3390/su17115062>
- Mehralian, H., Chieffo, N., Moritz, M., Gögen, B., Khodadadi, A., Amaral Ferreira, M., & Oliveira, C. S. (2024). Enhancing urban resilience in historical centers: A scenario-based approach to seismic risk and strengthening interventions. *Disaster Prevention and Resilience*, 3(4). <https://doi.org/10.20517/dpr.2024.13>
- Meletti, C., Stucchi, M., & Calvi, G. M. (2014). La classificazione sismica in italia, oggi. *Progettazione Sismica*, (3).
- Milutinovic, Z. V., & Trendafiloski, G. S. (2003). WP4: Vulnerability of current buildings. Institute of Earthquake Engineering; Engineering Seismology (IZIIS).

- Ministry of Development, Public Works and Administration. (2022). EVR platform: Rapid visual assessment of buildings. <https://evr.mdlpa.ro/en/>
National Program for the Consolidation of High Seismic Risk Buildings. Retrieved June 19, 2025.
- Minutolo, V., Cerri, E., Coscetta, A., Damiano, E., De Cristofaro, M., Di Gennaro, L., Esposito, L., Ferla, P., Mirabile, M., Olivares, L., & Zona, R. (2020). NSHT: New smart hybrid transducer for structural and geotechnical applications. *Applied Sciences*, 10(13), 4498. <https://doi.org/10.3390/app10134498>
- NCSEA. (n.d.). Insights from the 18th world conference on earthquake engineering (WCEE) 2024. <https://www.ncsea.com/news-post/insights-from-the-18th-world-conference-on-earthquake-engineering-wcee-2024/>
Retrieved June 18, 2025.
- Paoletti, B., Tanganelli, M., & Viti, S. (2024). Assessment of the seismic vulnerability of florence (italy) through macro-seismic methods. *Eng*, 5(4), 2821–2838. <https://doi.org/10.3390/eng5040147>
- Pavel, F., & Nica, G. (2024). The seismic evaluation of existing buildings for energy renovation—a case study for the residential building stock in bucharest (romania). *Buildings*, 14(6), 1742. <https://doi.org/10.3390/buildings14061742>
- Picchi, C. (2016). Valutazione del rischio sismico delle strutture esistenti [Doctoral dissertation, DIPARTIMENTO DI INGEGNERIA STRUTTURALE E GEOTECNICA].
- Pitilakis, K., Riga, E., Apostolaki, S., & Danciu, L. (2024). Seismic hazard zonation map and definition of seismic actions for greece in the context of the ongoing revision of EC8. *Bulletin of Earthquake Engineering*, 22(8), 3753–3792. <https://doi.org/10.1007/s10518-024-01919-8>
- Plessi, V., Bastianini, F., & Sedigh, S. (2007). A wireless system for real-time environmental and structural monitoring. In *Software technologies for embedded and ubiquitous systems* (pp. 456–465). Springer Link.
- Preethichandra, D. M. G. (2023). Influence of smart sensors on structural health monitoring and asset management: A review. *Sensors*, 23(18), 7779. <https://doi.org/10.3390/s23198279>
- Project, D. (2022). Database of damaged buildings after italian earthquakes (DaDO). ReLUIS. <https://www.reluis.it>
- QGIS Development Team. (2024). Qgis geographic information system (Version 3.34) [Open-source GIS software]. <https://qgis.org>
- QGIS Development Team. (n.d.). Qgis geographic information system [Software]. QGIS Association. Retrieved August 12, 2025, from <https://qgis.org>
- R Discovery. (n.d.). Rapid visual screening research articles. https://discovery.researcher.life/topic/rapid-visual-screening/18463497?page=1&topic_name=Rapid%20Visual%20Screening
Retrieved June 18, 2025.

- Rai, D. (2008). A generalized method for seismic evaluation of existing buildings. *Current Science Association*, 94, 363–370.
- ReLUIs Consortium. (2021). Seismic vulnerability assessment of the italian building stock: Summary of findings and future perspectives. ReLUIs – Rete dei Laboratori Universitari di Ingegneria Sismica. <https://www.reluis.it>
Technical Report, Italy.
- Rossetto, T., & Elnashai, A. (2003). Derivation of vulnerability functions for european-type RC structures based on observational data. *Engineering Structures*, 25(10), 1241–1263. [https://doi.org/10.1016/S0141-0296\(03\)00060-9](https://doi.org/10.1016/S0141-0296(03)00060-9)
- Roy, G., Dutta, S., & Choudhury, S. (2023). Building portfolio seismic fragility analysis: Incorporating building-to-building variability to carry out seismic fragility analysis for reinforced concrete buildings in a city. *Disaster Prevention and Resilience*. <https://doi.org/10.20517/dpr.2023.08>
- Ruggieri, S., Cardellicchio, A., Leggieri, V., & Uva, G. (2021). Machine-learning based vulnerability analysis of existing buildings. *Automation in Construction*, 132, 103936.
- Salencon, J. (1983). Limit analysis and rupture calculations. Presses of the National School of Bridges; Roads. <http://worldcat.org/isbn/2859780599>
- Spence, R., Kelman, I., Baxter, P., Zuccaro, G., & Petrazzuoli, S. (2005). Residential building and occupant vulnerability to tephra fall. *Natural Hazards and Earth System Sciences*, 5(4), 477–494. <https://doi.org/10.5194/nhess-5-477-2005>
- Stucchi, M., Meletti, C., Montaldo, V., Crowley, H., Calvi, G. M., & Boschi, E. (2011). Seismic hazard assessment (2003–2009) for the italian building code. *Bulletin of the Seismological Society of America*, 101(4), 1885–1911.
- Tataro, E. (2022). Protocol proposal of seismic risk maps through discontinuous fem limit analysis and numerical-based abacuses. [Doctoral dissertation, University of Campania-Luigi Vanvitelli.].
- Vicente, R., Ferreira, T., Maio, R., Costa, A., Estêvão, J., Varum, H., Costa, A., & Oliveira, C. (2014). Metodologia de avaliação da vulnerabilidade sísmica: Calibração e validação macrossísmica. *5as Jornadas Portuguesas de Engenharia de Estruturas*, 1–15.
- Wang, H., Guo, J.-K., Mo, H., Zhou, X., & Han, Y. (2023). Fiber optic sensing technology and vision sensing technology for structural health monitoring. *Sensors*, 23(9), 4334. <https://doi.org/10.3390/s23094334>
- Wang, R., & Li, J. (2025). Fast sparse representative tree splitting via local density for large-scale clustering. *Scientific Reports*, 15(1), 29398. <https://doi.org/10.1038/s41598-025-13848-w>
- Xofi, M., Ferreira, T. M., Domingues, J. C., Santos, P. P., Pereira, S., Oliveira, S. C., Reis, E., Zêzere, J. L., Garcia, R. A., & Lourenço, P. B. (2024). On the seismic vulnerability assessment of urban areas using census data: The lisbon metropolitan area as a pilot study area. *Journal of Earthquake Engineering*, 28(1), 242–265.

- Yakut, A., Altuğ, E., Alper, I., Haluk, S., & Sinan, A. (2013). Rapid seismic assessment procedures for the turkish building stock. *Seismic Evaluation and Rehabilitation of Structures*.
- Zacchei, E., & Molina, J. L. (2022). Probabilistic seismic hazard analysis for andalusian dams in southern spain using new seismogenic zones. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, 8(3), 04022034. <https://doi.org/10.1061/AJRUA6.0001249>
- Zienkiewicz, O. C., & Taylor, R. L. (2005). The finite element method for solid and structural mechanics. Elsevier.
- Zona, R. (2021). Discontinuous finite element limit analysis and semi-analytical procedures [Doctoral dissertation, Università degli Studi della Campania Luigi Vanvitelli]. XXXIV Cycle, Supervisor: Prof. Vincenzo Minutolo.
- Zona, R., Imani, H., Losco, S., Modano, M., & Minutolo, V. (2025). Fast evaluation of seismic vulnerability of rc building. a proposal of micro-zoning procedure for safety assessment. [In press]. *Natural Hazards*.
- Zuccaro, G., & Cacace, F. (2015). Seismic vulnerability assessment based on typological characteristics. the first level procedure “save”. *Soil Dynamics and Earthquake Engineering*, 69, 262–269.