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Reliability of Rapid Seismic Vulnerability Assessment of Italian Architectural Heritage: the case of Churches

*** [1] Lucio Nobile , [2] Mario Bonagura**
[1, 2] Laboratory LADS, University of Bologna, Cesena, Italy
[1] E-mail: lucio.nobile@unibo.it , [2] E-mail: mbonagura@unibo.it

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Abstract

Historical buildings play an important role in the cultural heritage conservation. The frequent occurrence of seismic events in Italy involves either the culture of preservation or the civil protection action aimed to reduce the risk to people and assets. Most of the Italian architectural heritage can suffer severe injuries during an earthquake. According to the ancient techniques, these masonry buildings withstand mainly gravity loads and are intrinsically vulnerable to stresses induced by the earthquakes. Italian Churches are a significant example of these typical buildings. They are vulnerable mainly due to their *typical* planovolumetric configuration in combination with *specific* local factors.
One of the main technical activities carried out by the Italian Civil Protection after an earthquake is to assess the damage in Churches and to evaluate their own vulnerability. To this end, qualified technicians perform a visual inspection. They then fill out ad hoc synthetic forms based on the collapse mechanisms that can be activated during an earthquake.
This study uses artificial intelligence techniques to evaluate the reliability of vulnerability assessments obtained using this rapid procedure.
Keywords: Architectural Heritage; damage assessment; seismic vulnerability evaluation; visual inspection; ANN approach; disaster seismic risk plan

1. Introduction

Italy's cultural heritage is well-known around the world. According to the list of invaluable sites for humanity created by UNESCO (United Nations Educational, Scientific and Cultural Organization), 61 sites are recognised as Intangible Cultural Heritage of Humanity. This list was drawn up following the World Convention concerning the Protection of World Cultural and Natural Heritage on 16 November 1972. Italy is at the top of the list. The Italian cultural heritage is immense. It consists of over 200,000 architectural, monumental and archaeological cultural assets, 3,400 museums and about 2,000 archaeological areas and parks.
The conservation and protection of Italy's historical and cultural heritage depend on the physical characteristics of the territory in which it is located. In this sense, natural hazards of hydrogeological and seismic origin seriously threaten the Italian territory, very often in combination with each other (Nobile, L. 2023). Italy is characterized by a high exposure to seismic hazards. Seismic hazard is a measure of the probability of an earthquake of a certain intensity occurring in each geographical area within a given period. The seismic hazard map of the Italian Territory is reported in Figure 1 (Stucchi, M. et al. 2011). Church buildings made of masonry are a fundamental component of Italy's and Europe's historic built environments. They represent not only an architectural heritage of great artistic value, but also a defining element of local communities' identities. However, these buildings are particularly vulnerable to seismic activity due to the materials' and construction techniques' intrinsic characteristics. Masonry churches are typically built with unreinforced masonry systems, which are characterized by limited tensile strength and brittle behavior. Complex geometric configurations, such as longitudinal naves, apses, transepts, bell towers, and vaulted roofs, make it difficult to describe their structural behavior using simple models. During seismic events, these buildings often exhibit localized damage mechanisms related to the loss of equilibrium in individual structural components rather than global collapse. In recent decades, the study of the seismic vulnerability and risk of masonry churches has become a central focus of structural research, particularly in Italy, where significant historic heritage coexists with a high level of seismic hazard. Following the 1980 Irpinia earthquake and especially after the Umbria-Marche (1997), L'Aquila (2009), and Central Italy (2016–2017) earthquakes, numerous analytical methodologies have been developed to understand damage mechanisms and assess the safety of these structures.
Studies have shown that masonry churches behave in a manner strongly influenced by local collapse mechanisms linked to the loss of equilibrium of structural macro-elements, such as facades, longitudinal walls, and apses, rather than by global failures of the building structure. In this context, the "macro-element" approach (Casapulla,C. et al.

2025,Formisano,A. et al 2025) allows for the systematization of church behavior by identifying potential kinematic mechanisms and verifying their activation through kinematic analysis.

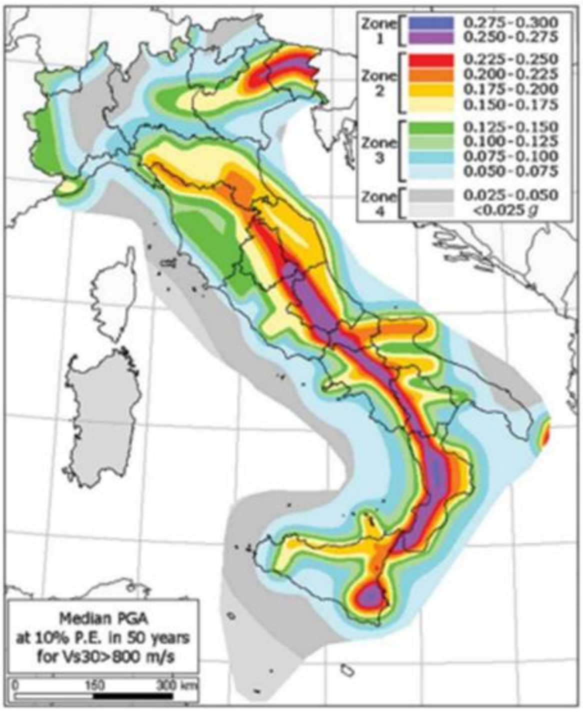


Figure 1: Seismic hazard map of Italy.

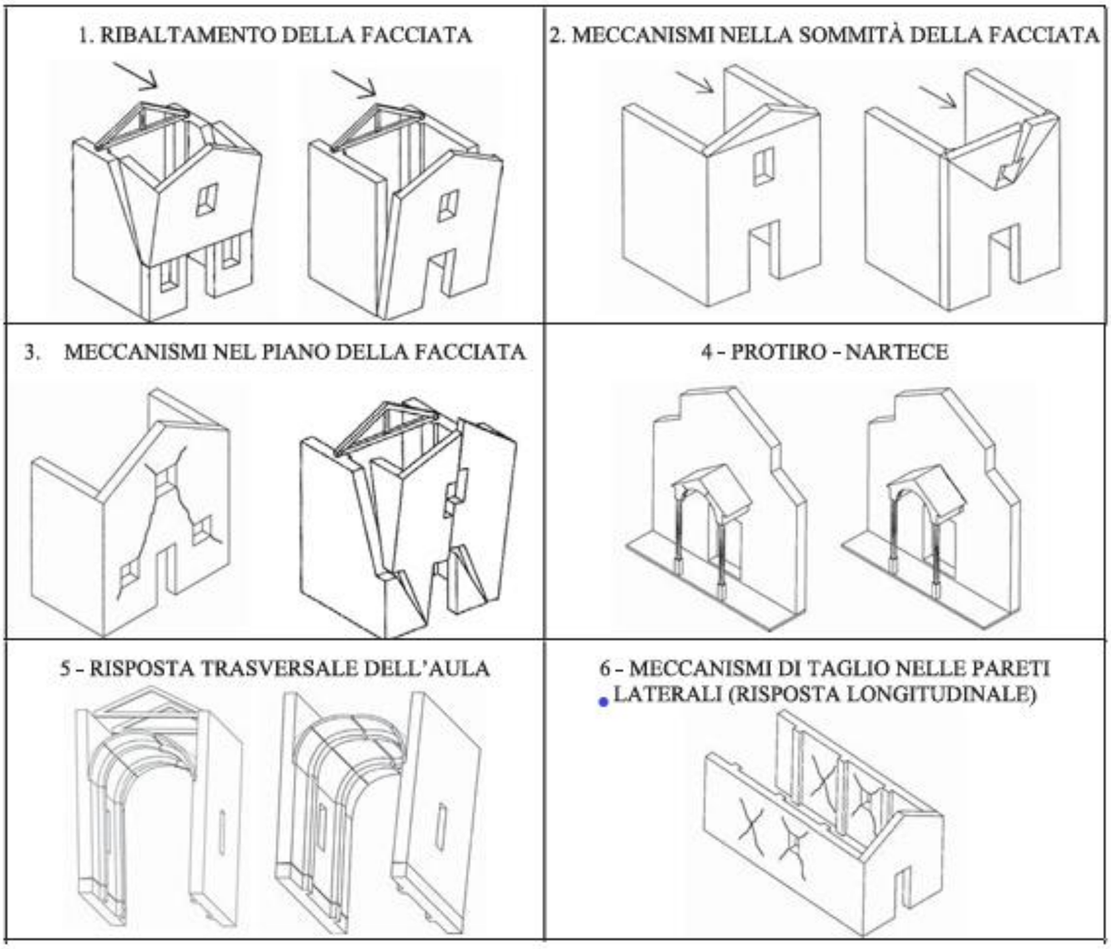
This methodology has been progressively integrated into Italian regulatory procedures and the Guidelines for Cultural Heritage, which provide various levels of detail ranging from simplified analyses to advanced numerical modeling. The analysis of damage observed following the most recent earthquakes makes a significant contribution. Despite advances in assessment methodologies, this analysis shows that ecclesiastical heritage continues to exhibit high levels of vulnerability.
This evidence confirms the need to strengthen seismic prevention and retrofitting strategies, prioritizing interventions compatible with conservation principles based on a thorough understanding of structural behavior.
In summary, the state of the art demonstrates that the seismic risk assessment of masonry churches is a well-established yet continually evolving field of research. The integration of simplified and advanced approaches, empirical data, and numerical modeling is essential for ensuring structural safety and protecting historical and artistic heritage.
After a seismic event, one of the issues that needs to be addressed is the rapid, accurate and reliable assessment of damage. This information is useful for managing and coordinating immediate measures for the safety of people and the evacuation of buildings damaged by the earthquake. This assessment is carried out by technicians using traditional methods based on visual inspection and recognized damage mechanisms.
The observation of post-earthquake damage to Friuli churches after the 1976 earthquake (Doglioni,F. et al. 1994) determined the development of a vulnerability analysis methodology involving filling in a detailed form covering three phases:
a) Description of geometry, materials and cracked framework.
b) Subdivision of the building into recognizable, unitary macroelements in terms of seismic response (façade, apse, bell tower, etc.).
c) Identification of possible modes of damage and collapse mechanisms associated with each macroelement. This methodology enables the damage caused by the earthquake to be examined rapidly and schematically. The last version of this form has been approved by the President's Decree of the Council of Ministers on 23 February 2006, published in the G.U. of 07 March 2006 n. 55 (D.P.C.M. 23 febbraio 2006). Note that in this last version the collapse mechanisms increase from 18 to 28, as reported in the following Atlas.
According to this methodology, the seismic vulnerability is represented by an index Iv, which varies between 0 and 1, empirically defined in (Guidelines for the Evaluation and Reduction of Seismic Risk of Cultural Heritage,2011) as

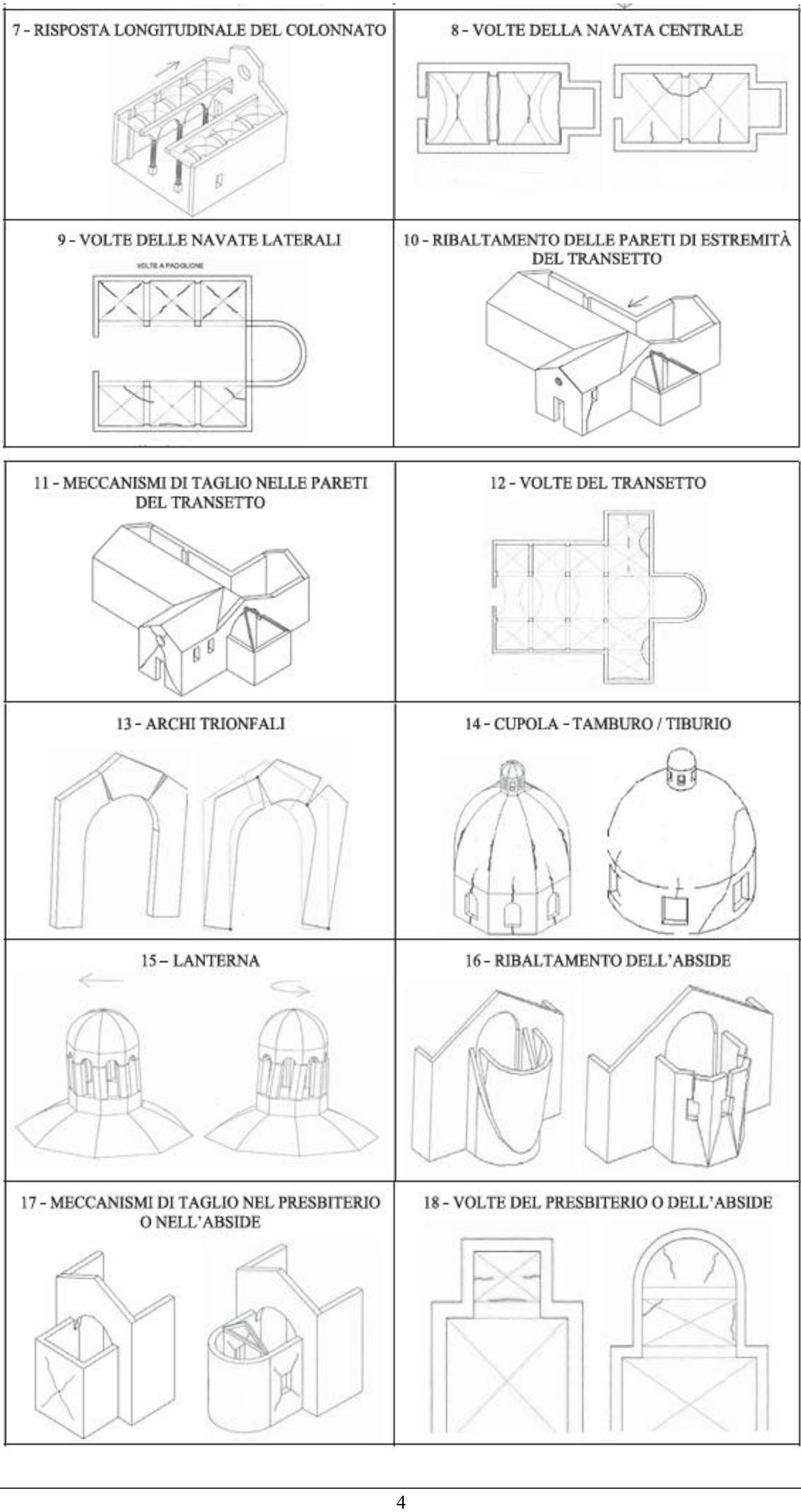
$$I_v = \frac{1}{6}\frac{\sum_{k=1}^{28}\rho_i(v_{ki}-v_{kp})}{\sum_{k=1}^{28}\rho_i\rho_k} + \frac{1}{2}$$ **Equation 1.** Vulnerability index.

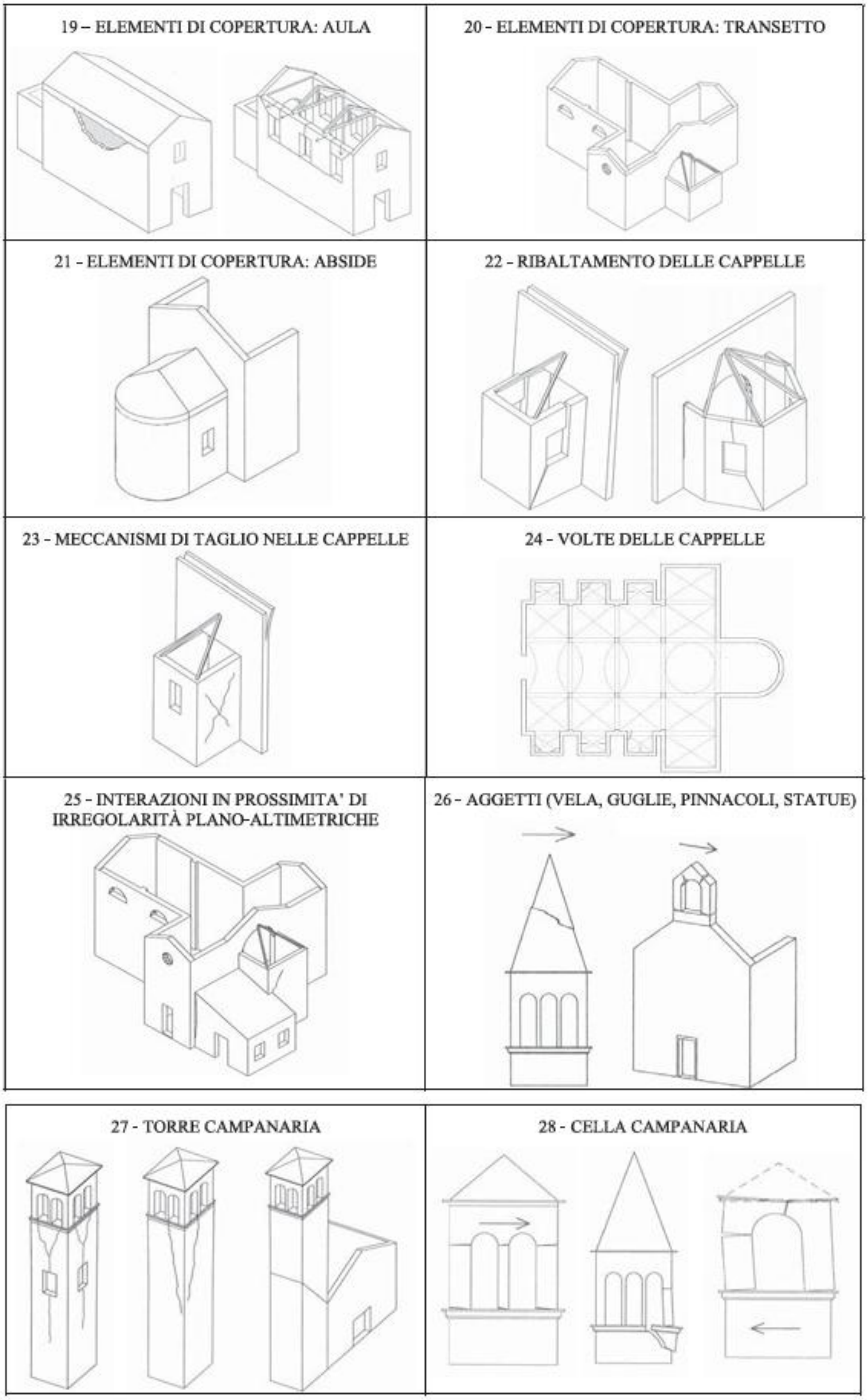
For the i-th mechanism, the terms v_{ki} and v_{kp} are the scores obtained from the assessment of vulnerability indicators and anti-seismic measures (provided by the guidelines themselves). The weight assigned to the mechanism (ρ_k) takes value zero for mechanisms that cannot be activated due to the lack of the macro element, and a value between 0.5 and 1 in all other cases.
An estimate made in this way is purely statistical, but this approach can be considered valid when applied to a territorial analysis for prevention purposes. Specifically, the vulnerability of churches is assessed using a simplified vulnerability

index calculated based on typological and construction parameters measured on site. This index enables rapid classification of buildings and is subsequently converted into fragility curves (Aminifar, E. et alter 2026, Casapulla, C. et al.2025), which are necessary for probabilistic damage analysis
The methodology also involves defining exposure through a georeferenced inventory of churches and using the above national seismic hazard model (INGV MPS04). Integrating these elements into the IRMA platform (Lagomarsino, G.,Masi A. 2024, Faravelli,M. et al. 2024) allows for the simulation of damage scenarios and the production of risk maps at the regional level. IRMA is a flexible, scalable, and scientifically advanced platform developed by Eucentre (European Centre for Training and Research in Earthquake Engineering)for the Italian Department of Civil Protection .It integrates data, models, and tools to generate seismic risk analyses The results make it possible to identify the most critical areas and support the planning of mitigation measures, highlighting how the use of the vulnerability index represents an effective compromise between ease of application and reliability of results.
In conclusion, although it introduces a certain degree of approximation, adopting a simplified vulnerability index represents an effective methodological solution for large-scale analyses. When properly calibrated, including with empirical data such as that in the Da.D.O. database (Observed Damage Database), it reliably estimates the seismic vulnerability of churches and derives the corresponding fragility curves. As described in (Calderini,C. et al. 2022, Longobardi,G. et al.2025, Onescu,U. et al. 2025), the Da.D.O. project was designed to collect, catalog, and compare data on the damage and structural characteristics of buildings inspected after major earthquakes in Italy since the 1976 Friuli earthquake. Integrating this information with seismic hazard models and the exposure inventory within the IRMA platform allows for the creation of nationwide seismic risk maps. These maps are a fundamental tool for developing disaster risk management plans because they identify priority areas and buildings for mitigation measures, optimize resource allocation, and improve emergency response capabilities.
Artificial Intelligence, including the Artificial Neural Network (ANN) approach is a nonparametric statistical tool without knowing the theoretical relationships between the input and the output. ANN approach with feasible prediction has been already employed in (Bonagura, M., Nobile,L. 2021, Seyed et al. 2024) to determine concrete compressive strength using input variables such as age, Portland cement, water, sand, etc.

Atlas of Collapse Mechanisms in Churches provided in the A-DC survey form




7 - RISPOSTA LONGITUDINALE DEL COLONNATO
8 - VOLTE DELLA NAVATA CENTRALE
9 - VOLTE DELLE NAVATE LATERALI
VOLTE A PADIGLIONE
10 - RIBALTAMENTO DELLE PARETI DI ESTREMITÀ DEL TRANSETTO
11 - MECCANISMI DI TAGLIO NELLE PARETI DEL TRANSETTO
12 - VOLTE DEL TRANSETTO
13 - ARCHI TRIONFALI
14 - CUPOLA - TAMBURO / TIBURIO
15 – LANTERNA
16 - RIBALTAMENTO DELL'ABSIDE
17 - MECCANISMI DI TAGLIO NEL PRESBITERIO O NELL'ABSIDE
18 - VOLTE DEL PRESBITERIO O DELL'ABSIDE



The aim of this paper is to verify the accuracy of the estimated Vulnerability index employing ANN approach, comparing the estimated values with that based on this modern approach.
The aim of this paper is to verify the accuracy of the calculated vulnerability index. This will be done by comparing some values with those based on the ANN approach.

2. Materials and Methods

Artificial Neural Networks (ANNs) are information-processing systems that attempt to simulate the behaviour of biological nervous systems, which consist of many neurons connected in a complex network, in a computer program (Mienye, I. D., & Swart, T. G. 2024, Muñoz-Zavala, A.E. et al. 2024).). The average number of connections that a neuron has is approximately ten thousand. Therefore, there are hundreds of billions of connections. Intelligent behaviour arises from the interactions between these interconnected units. Some of these units receive information from the external environment (i.e. the input layer), some emit responses into the environment (i.e. the output layer), and some communicate only with other units inside the network (i.e. the hidden layer). Refer to Figure 2, which shows this schematically. The network's input-output ratio, i.e. its transfer function, is not programmed, but obtained through a learning process based on empirical data.
There are several types of artificial neural network (ANN), which are categorised by the type of connections between neurons in different layers, the activation functions, and the learning algorithms. Depending on the connections between the artificial neurons, three main classes of ANN can be distinguished: feed-forward networks, cellular networks, and feedback networks.

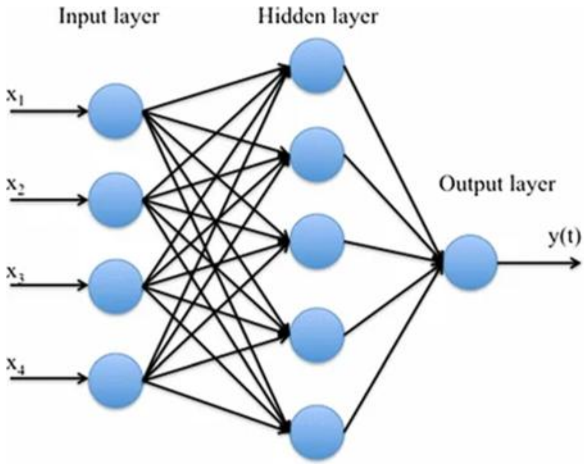


Figure 2: Schematic representation of a three-layer ANN.

One of the most important aspects of a neural network is its learning process. There are three main types of learning: i) supervised learning, ii) unsupervised learning and iii) reinforcement learning. From a mathematical point of view, learning in a neural network involves finding a minimum of a function in an n-dimensional space. This function is determined by the variation in error based on the network's weights. The algorithm used for supervised learning is backpropagation, which minimises the network's total error by modifying the weights of the connections.
There are many types of neural network, which are differentiated by basic characteristics such as:
a) the intended use
b) the activation function
c) the learning method (and consequently the learning algorithm)
d) the connection architecture
Three basic categories can be distinguished from the point of view of use.

- Associative memories: a neural network that can learn associations between different patterns (a complex set of data, e.g. the pixels of an image), so that presenting a pattern α results in pattern β being output, even if pattern α is imprecise or incomplete (noise resistance).
- Simulators of mathematical functions: they can understand the function that links the output with the input according to the examples given (target data) during the learning phase. After the learning phase, the network can provide an output in response to an input that is different from those used in the training examples.
- Classifiers: they are neural networks that classify data into specific categories based on characteristics that are similar. This last type of network does not involve unsupervised learning, in which the input data are distributed into categories that are not predefined. The learning algorithm of a neural network depends on how it is used, as well as on the architecture of the connections.

The most fundamental classification for defining its structure is certainly that relating to the architecture of the connections. From the perspective of the connections between neurons, three basic categories can be distinguished:
a) Feed-forward neural network (FFN)
b) Cellular neural network (CNN)
c) Feedback neural network (FBN).
The Feed-Forward Network (FFN) is the simplest and most widely used typology, consisting of more than two layers of neurons. In other words, the input and output layers are supplemented by one or more hidden layers. In this type of neural network, each neuron is connected to all the neurons in the previous layer, but not to the neurons in its own layer. The signal propagates unidirectionally from the input layer to the output layer through the hidden layer.
These networks are generally used in supervised learning methods and training, e.g. the backpropagation error algorithm.

One example of this type of neural network is the radial basis function (RBF) network (Ding,G. et al. 2026). RBF neural networks are a $particular\ type\ of\ feed-forward\ network\ with\ a\ single\ hidden\ layer.$
Cellular neural networks (CNNs) are characterised by the fact that individual neurons are only connected locally to their neighbours. These bidirectional connections affect neurons in the immediate vicinity. They are described by nonlinear differential equations, and their natural field of application is real-time image processing (Putra, M., Phinn,S. 2026) . The parallel architecture of such networks makes them particularly suitable for real-time applications, while their two-dimensional structure makes them well-suited to image processing.
Feed-back networks (FBNs) have connections between different neurons that are either direct or indirect, depending on whether they are related to the recursive single unit or the layer to which the unit belongs. In this case, the output determined by the network is partially reinstated in the system at the end of a succession of iterations, creating a feedback circuit. One of the most widespread feedback networks is Hopfield's network, which is usually used in reproduction systems (Agliari,E. et al. 20126).
All neural networks have neurons as their fundamental building blocks. This applies to both biological and artificial neural networks. The neurons can be seen as elementary information-processing units characterised by connections (synapses) w_{ij} that are able to transfer signals (stimuli) a_i to other neurons. The synaptic weights w_{ij} represent the relative importance of their inputs. Each neuron sums its weighted inputs $w_{ij}\, a_j$, emitting an output y which varies according to the specific activation function chosen. To better understand how a neural network operates, the concept of an activation function f must first be introduced in mathematical terms.

$$a_i = f\left(\sum_j w_{ij} a_j\right) \quad \textbf{Equation 2.}\ \text{Activation value}$$

where w_{ij} is the synaptic and a_i is the activation value. This transfer function therefore allows the receiving neuron to transmit the received signal by modifying it. There are many different types of activation function in literature. The most used for computational analysis are: Linear function, Threshold function, Sigmoid logistic function, Hyperbolic tangent function, Rectified linear unit function.
When applying a neural network system to solve a specific problem, the values of the synaptic weights are the first unknown parameters to be determined. To determine the value that minimises the network's total error, a learning (or training) process must be carried out. This process can be one of three main types:

1. Supervised learning: a data set is used for training that includes examples of typical input and output, to enable the network to 'learn' the relationship between them. The network is then trained using a suitable algorithm that modifies the synaptic weights to minimise the prediction error relative to the training set. If the training is successful, the network learns to recognise unknown relationships between input variables and output results. It can therefore make predictions in cases where the output is unknown. In other words, the aim of this type of learning is to predict the output value for each valid input based on a limited number of examples of correspondence.
2. Unsupervised learning is based on algorithms that modify the synaptic weights of the network using a dataset that only includes the input parameters. Unsupervised learning is often used to develop data compression techniques.
3. Reinforcement learning is like supervised learning but differs in that there is no input-output relationship. This can be substituted with suitable algorithms capable of identifying the most effective approach.

To minimize the total error of the network, a process of learning (or training) must be carried out. In the supervised learning process, the aim is the prediction of the output value for each valid input data, based only on a limited number of examples of correspondence.
From a mathematical point of view the learning process consists of finding a minimum of a function in a n-dimensional space. This function is given by the variation of the error based on the weights of the network. The most effective and widespread technique used in the learning with more supervision is the backpropagation error algorithm, which minimizes the total error of the network through the modification of the weights of the connections. To search for a minimum, it is usually used the gradient descent technique. The algorithm most used in the supervised learning is the backpropagation error algorithm (BPE), which through the modification of the synaptic weights of the connections minimizes the total error of the network.

3. Results

The artificial neural network used in this study is a multilayer feedforward network, also known in literature as a Multilayer Perceptron (MLP) (Wang et al.,2026). The network consists of three main layers:
● an input layer consisting of N = 28 neurons, each associated with an input variable (28 collapse mechanisms);
● a hidden layer consisting of 28 neurons;
● an output layer consisting of a single neuron, responsible for producing the network's output (Vulnerability Index).
Each neuron computes a linear combination of inputs. A nonlinear activation function is applied to this combination.
The neural network was trained using the backpropagation algorithm, which is based on minimizing a cost function. In this network, the mean squared error (MSE) was used. The Levenberg–Marquardt algorithm was used for training (Osman Mohammed A.W., Mohamed K.A. 2026). It is an advanced variant of backpropagation. It approximates Newton's method.
To properly evaluate the model's performance and reduce the risk of overfitting, the dataset was divided into three subsets:
Training set: Used to update the weights.

Validation set: Used to monitor error during training.
Test set: Used for the final performance evaluation.
The division was performed randomly according to the following percentages:
Training: 70%;
Validation:15%;
Test: 15%.
The early stopping criterion halts training when the error on the validation set begins to increase, indicating a loss of generalization ability. This mechanism helps produce a more robust model by preventing it from overfitting the training data.
To derive vulnerability indices using the ANN approach, ten case studies were simulated with arbitrary weights assigned to each of the 28 mechanisms, as shown in the ten columns of Table 1.
The penultimate row shows the vulnerability indices calculated using the empirical formulation (Italian Guidelines), i.e., Equation 1. The last row shows the indices derived from the use of the Artificial Neural Network (ANN).

Table 1: Ten Case Studies Italian Guidelines Equation (IGE) vs Artificial Neural Network (ANN)**.**

	A	B	C	D	E	F	H	I	L	M
1	1	2	1	1	1	1	2	1	3	3
2	1	2	1	1	1	2	2	1	3	3
3	1	2	1	1	1	3	2	1	3	3
4	1	2	1	1	1	1	2	1	3	3
5	1	2	1	2	1	2	2	1	3	3
6	1	2	1	2	1	3	2	3	3	3
7	1	1	1	2	1	1	2	3	3	3
8	1	1	1	2	1	2	2	3	3	3
9	1	1	1	3	1	3	2	3	3	3
10	1	1	1	3	1	1	2	3	3	3
11	1	1	1	3	1	2	2	3	3	3
12	1	1	1	3	1	3	2	3	3	3
13	1	1	1	1	1	1	2	3	3	3
14	1	1	1	1	1	2	2	3	3	3
15	1	1	2	1	3	3	2	3	3	3
16	1	1	2	1	3	1	2	3	3	3
17	1	1	2	2	3	2	2	3	2	3
18	1	1	2	2	3	3	2	3	2	3
19	1	1	2	2	3	1	2	3	2	3
20	1	1	2	2	3	2	2	3	2	3
21	1	1	2	3	3	3	2	3	2	3
22	1	1	2	3	3	1	2	3	2	3
23	1	1	2	3	3	2	2	1	2	3
24	1	1	2	3	3	3	2	1	2	3
25	1	1	2	1	3	1	2	1	1	3
26	1	1	2	1	3	2	2	1	1	3
27	1	1	2	1	3	3	2	1	1	3
28	1	1	2	1	3	1	2	1	1	3
I_v IGE	0,6667	0,7077	0,7359	0,7965	0,8052	0,82251	0,8333	0,8658	0,9113	1
I_v ANN	0,6607	0,7054	0,7358	0,7943	0,808	0,8223	0,8352	0,8646	0,9106	0,9888

4. Discussion
The results obtained from the proposed neural network suggest that the vulnerability indices calculated on a statistical basis are reliable. Research carried out on damaged churches has resulted in the identification of two classes of vulnerability: typical and specific. The former is related to the planovolumetric configuration of the building, the latter to local weakening factors. Therefore, the vulnerabilities associated with the various mechanisms should be considered typical due to their relationship with the planovolumetric configuration. The specific vulnerabilities depend on conditions of local or generalized vulnerability related to initial non-standard construction, building transformation processes that are likely to weaken the building, structural deterioration and maintenance debts, and insufficient structural improvements to counter past disturbances. The ANN approach is the only one that can take specific vulnerabilities into account. It does so by incorporating these vulnerabilities as additional input indices into the neural network. Therefore, this methodology is the only one that provides a thorough evaluation of all potential vulnerabilities that could compromise the seismic safety of churches. Integrating simplified approaches and advanced analytical tools provide reliable and useful results that support seismic prevention policies. This contributes to preserving cultural heritage and reducing risk at the regional level. To ensure both human safety and the preservation of historic and religious assets in seismic events a Disaster Seismic Risk Plan for churches must include:
Seismic Risk Assessment: Identify earthquake hazards and evaluate the vulnerability of the building, structure, and cultural assets.
Structural Prevention Measures: Strengthen the building through seismic retrofitting and secure non-structural elements (altars, statues, decorations).
Protection of Cultural Heritage: Stabilize and protect artworks, liturgical objects, and archives from earthquake damage.
Emergency Preparedness: Define evacuation procedures, roles, and coordination with emergency services.
Monitoring and Maintenance: Regular inspections and structural monitoring to detect weaknesses.
Emergency Response Actions: Immediate steps to ensure safety and reduce damage during and after an earthquake.
Recovery Planning: Post-event assessment, restoration of the church, and reopening of activities.

5. Conclusions
After a seismic event, one of the issues that needs to be addressed is the rapid, accurate and reliable assessment of damage in Churches and to evaluate their own vulnerability This information is useful for managing and coordinating immediate measures for the safety of people and the evacuation of buildings damaged by the earthquake. This assessment is carried out by technicians using traditional methods based on visual inspection and recognized damage mechanisms. They fill out ad hoc synthetic forms based on the collapse mechanisms that can be activated during an earthquake. These forms make it possible to empirically assess the church’s vulnerability index.
This index is useful for developing risk maps on a regional basis, which are necessary for disaster risk management plans. The reliability of the index has been positively evaluated using an Artificial Neural Network (ANN) approach.
In conclusion, the proposed modern methodology shows that the empirically evaluated seismic vulnerability index is reliable for churches. The Seismic Risk Assessment stage is crucial for the safeguarding of churches because it forms the basis for all subsequent decisions.In particular, it is important because:
It allows us to understand the actual vulnerability: churches are often historic buildings with complex and fragile structures; seismic assessment identifies weak points (naves, bell towers, roofs, frescoes).
It guides prevention measures: without a proper assessment, it is not possible to design effective strengthening or safety interventions.
It protects cultural heritage: it helps identify the most vulnerable artworks and plan specific protection measures.
It reduces damage and future costs: acting based on accurate analysis helps prevent collapses, irreversible losses, and expensive restoration work.
It improves people’s safety: it helps prevent dangerous situations for worshippers, visitors, and staff.
It supports emergency management: it provides useful data for planning evacuations and intervention priorities.
In summary, Seismic Risk Assessment is essential because it transforms a reactive approach into a preventive and informed one, ensuring more effective protection of churches and their historical and spiritual value.

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Conflicts of Interest
The authors report no conflicts of interest.

Data Availability Statement
The authors declare that the data supporting the findings of this study are available within the paper

CRediT Author Statement
Conceptualization,L.N.&M.B.; Methodology.M.B.; Writing – original draft,L.N.; Writing – review & editing, L.N. All authors have read and approved the final manuscript

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