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MASONRY BUILDINGS RECONSTRUCTION COST POST-EARTHQUAKE ANALYSIS WITH MACHINE LEARNING

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Abstract. *Machine learning (ML) methods represent advanced probabilistic data-driven techniques that can potentially empower earthquake engineering-related practices thanks to their ability to analyze hidden patterns buried in data. In this study, the authors examined the adoption of ML classification models for predicting reconstruction costs observed after L'Aquila 2009 earthquake event in the Abruzzi region based on masonry building vulnerability indexes and usability classes. The latter data mainly refers to the Rapid Post-Earthquake Damage Evaluation (AeDES) forms surveys, containing about 60 categorical features. Additionally, seismic intensity measures (IMs) have been incorporated into the database to encompass physics-based data characterizing the input demand. After an initial exploratory data analysis, the authors conducted some preliminary analysis on using the sole vulnerability index data for predictive purposes of the reconstruction costs using random forest algorithms. This approach could potentially benefit public administrations for long-term optimal resource earmarking on a regional scale. Indeed, preliminary findings from this study underscore the potential of using those ML-assisted procedures for quick simulation scenarios based on various reconstruction cost classes, contributing to cost-effective planning and seismic risk mitigation strategies. However, in this preliminary work, the AeDES usability data have not been considered due to the purely predictive purpose conjecture carried on in this study. Therefore, future promising developments should also combine the vulnerability index information and the observed building usability classes, to improve the extrapolation performance of ML-assisted predictive tools.*

Keywords: Machine learning, Masonry building, Post-earthquake usability class, Post-earthquake reconstruction costs

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1 INTRODUCTION

The safeguard of the built environment against earthquake scenarios relies on the fundamental procedures of seismic risk assessment (SRA), such as the performance-based earthquake engineering (PBEE) framework [16, 11]. In risk assessment, three main actors are generally involved (mathematically speaking, integrated through a convolution integral): hazard, vulnerability, and exposure (or exposed asset). Earthquake hazard can be computed using probabilistic methods for seismic hazard (PSHA) [6] or scenario studies [26]. Vulnerability represents those conditions that may affect the susceptibility to the impacts of hazards [26]. These methodologies employ either mechanical or empirical foundations to assess the vulnerability of buildings and utilize socio-economic and demographic data to estimate exposed asset value, thus often referred to as socioeconomic vulnerability of exposed people [26]. Moreover, building damage is evaluated with fragility functions, i.e. probabilistic functions of exceeding various damage levels for a given earthquake intensity. The developed analytical methods leverage numerical models to replicate the response of building prototypes to seismic forces. Instead, pure empirical methodologies are commonly based on post-seismic event data to provide a grounded understanding of predicted damages. Therefore, based on all the above-mentioned aspects, the main goals of SRA are not only to safeguard human life but also to quantify seismic expected losses and potential reconstruction costs because they can strongly affect the financial statements and thus the socio-economic equilibrium of the whole society [20]. Indeed, providing predictive effective tools of the seismic loss and reconstruction costs may benefit administrative bodies for optimizing resource planning over time, dedicated investment for damage reduction at the regional scale, insurance purposes, etc.

To this date, the existing scientific literature reveals that the majority of post-earthquake observation data have been primarily used for structural aspects and fragility curve estimates. Conversely, fewer scientific studies have been focused on vulnerability assessment for estimating reconstruction costs [19, 13]. Some scholars have compared estimated repair costs with actual expenses from events such as the 2009 L'Aquila earthquake in Italy [12, 14] to identify the limitations of applying PHSA methodologies to various building types. Some authors, such as Agha Beigi et al. (2015) [1], employed the FEMA P-58 methodology [16] to assess losses for typical Italian frame structures. However, due to the lack of fragility and consequence functions tailored to non-U.S. nonstructural components in the original database, these studies had to use elements based on U.S. construction practices [24]. Refinements and validations have since been made to fragility and consequence functions to provide more accurate repair cost estimates for Mediterranean building stock [10, 25]. Recently, machine learning (ML) techniques and widespread use across various research fields have determined and fostered data-driven revival in earthquake engineering state-of-the-art research, e.g., for estimating key consequence parameters following a seismic event [23, 4]. This has included usability classifications and, more generally, damage metrics [5, 3].

To the best of the authors' knowledge, to this date, no existing research has used observed data after the 2009 L'Aquila earthquake in Italy to explore the potential for developing data-driven ML predictive models for estimating reconstruction costs of masonry buildings. Therefore, in this preliminary study, the authors compared various ML models for predicting masonry building reconstruction costs following the 2009 L'Aquila earthquake. Due to the complexity of obtaining accurate predictions of masonry buildings' seismic response, conventional methods are often used for vulnerability assessment and response estimation. Thus, exploring data-driven approaches to estimate reconstruction costs based on selected vulnerability indices representative of masonry buildings is a reasonable goal, in line with the reconstruction grant allocation procedure used after the 2009 L'Aquila earthquake. As highlighted by Fung et al. [17], cost predictions must encompass structural costs and additional direct and indirect expenses, such as permit fees and relocation costs, which are inherent in any major construction project. Indeed, the authors considered the total reconstruction costs granted in the current document.

The present study is organized as follows. In section 2, the reconstruction grant assignment procedure is briefly described in order to illustrate the available data used in the present study. In section 3, the ML framework herein considered has been described, and the preliminary results are discussed in section 4, followed by the overall conclusions and future improvement remarks.

2 RECONSTRUCTION COSTS DATASET FOR L'AQUILA 2009 EARTHQUAKE

The herein considered dataset refers to the 6.3 magnitude L'Aquila earthquake event that occurred on April 6th, 2009, in the Abruzzi region in Italy [2]. This event is sadly infamous in Italy for its destructive consequences and devastating social impact due to its about 300 fatalities and over 1,500 injuries, and about 70 thousand people displaced [15]. To further underline the extremely negative impact of such an event, in the immediate post-disaster earthquake instants, an initial estimate of the economic losses was about 10 billion euros [15].

Although this earthquake involved more than 124 Italian municipalities, the municipalities that experienced the most devastating effects have been named Municipalities of the Crater (MIC). This MIC municipalities list permits the government to identify and prioritize those struck areas to which public reconstruction funding is mainly dedicated. This study refers to data collected on buildings located in a concentrated area close to the epicenter of L'Aquila city, i.e., focusing on 11 municipalities belonging to the MIC list, as illustrated in Fig. 1 (a). Specifically, the available dataset consists of about 2230 buildings distributed in the 11 MIC considered municipalities.

The procedure for assigning reconstruction grants starts with rapid post-disaster comb visual surveys of professional engineers tasked to judge the buildings usability and observed damage. Since 1997 and subsequent amendments, during these surveys in Italy, the inspectors fill out the AeDES forms, i.e. the rapid post-earthquake damage evaluation forms. Divided into 9 sections, these forms deliver about 60 categorical features to support the inspector's judgment of the safety of the structure, categorized in classes from A to F. In reality, only four classes can be considered actual damage classes, i.e., A (immediately usable), B (usable after light restoration interventions), C (partially unusable building), and E (unusable building). The available usability data distribution over the inspected buildings in 11 MIC municipalities herein considered is illustrated in the pie chart of Fig. 1 (b). Almost 70% of the considered buildings have been classified as unusable, therefore with evident structural safety deficiencies. Therefore, for those E-classified buildings, it could be advisable to expect a great amount for the reconstruction grant, whilst for immediately usable A-class buildings, expect a much lower amount or virtually zero. However, this type of linear reasoning appears erroneous when inspecting the actually recognized grant amounts, see Fig. 1 (d). Indeed, the final grant amount accounts for many other aspects, such as refurbishment interventions for nonstructural elements. For instance, an A-classified building without evident safety issues but with extensive and diffused cracks in the whole plaster could theoretically be justified in receiving a great amount of the public grant. Indeed, reconstruction grants are practically computed starting from a "*base grant*" amount (700, 1000, 110, and 1270 euros/m^2), determined on the building AeDES usability class, a building global damage level indicator, and the building vulnerability index. Thereafter, as reported in

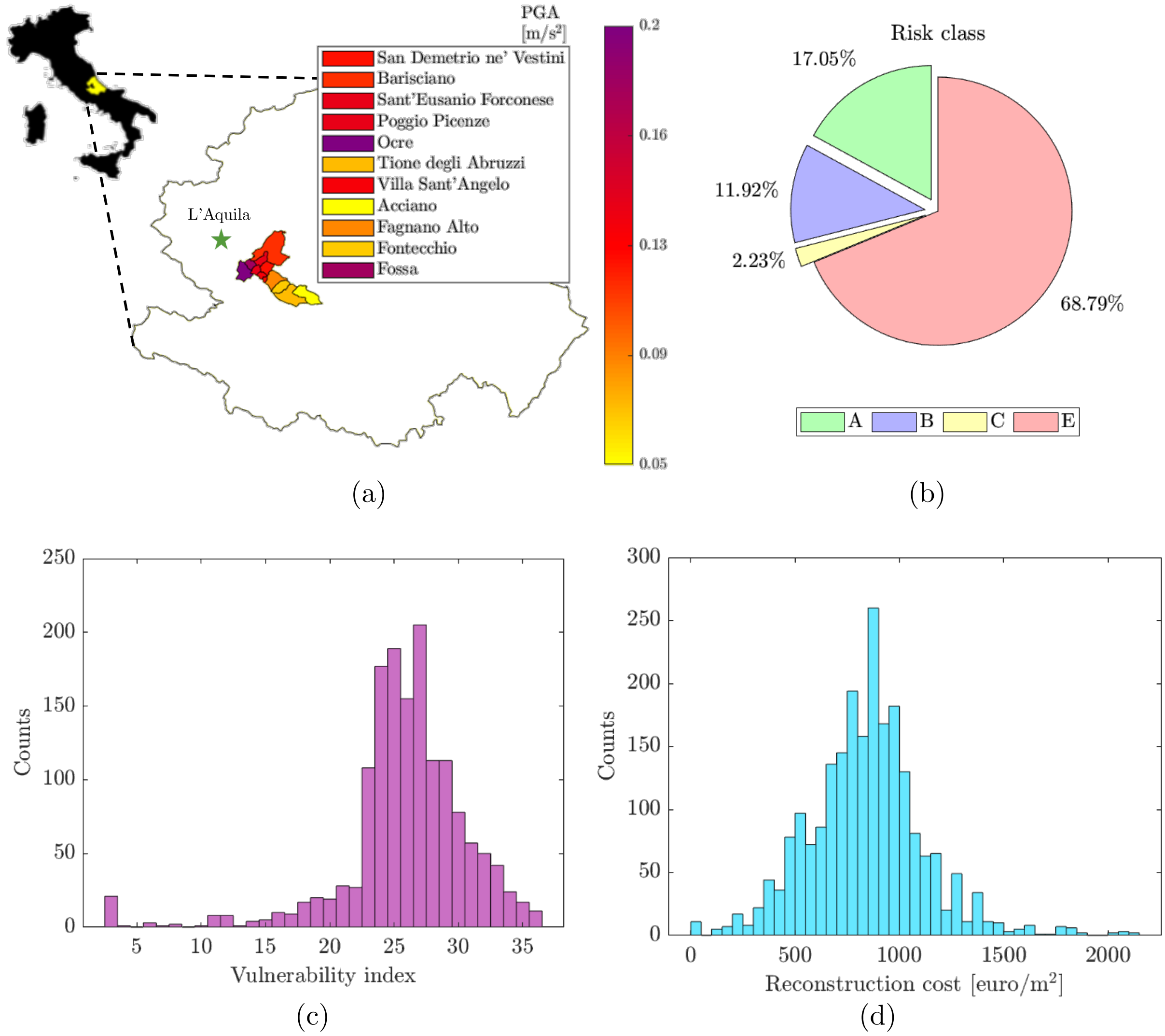

Figure 1: Dataset description. (a): PGA of municipalities under investigation assumed as intensity measure of L'Aquila 2009 earthquake; (b): AeDES building usability pie chart for classes A, B, C, and E; (c): buildings simplified global vulnerability index count bar chart; (d): post-event granted reconstruction costs count bar chart, expressed in euros per square meter.

[27], the base grant amount can be further adjusted case-by-case for several reasons, encompassing, e.g., special restoration interventions due to historical, artistic, or cultural significance, or specific engineering and architectural challenges, special construction difficulties, etc.

Starting from the AeDES form data, a global building damage level is assessed based on the EMS98 scale, eventually resulting in five indicators, i.e., Light Damage (D_1), Moderate Damage (D_2), Medium-Severe Damage (D_3), Severe Damage (D_4), and Extremely Severe Damage (D_5). As mentioned before, the definition of the exact base grant amount should also account for a global vulnerability index. This is a synthetic indicator denoted as V_1 (low vulnerability), V_2 (medium vulnerability), and V_3 (high vulnerability), computed by summing up single vulnerability scores regarding some structural elements categories identified for the specific structural typology under consideration. For masonry buildings, the sole typology considered in the current study, the global vulnerability index is determined by summing up scores of 9 different aspects [27]. Each of them can assume three possible values with increasing amounts

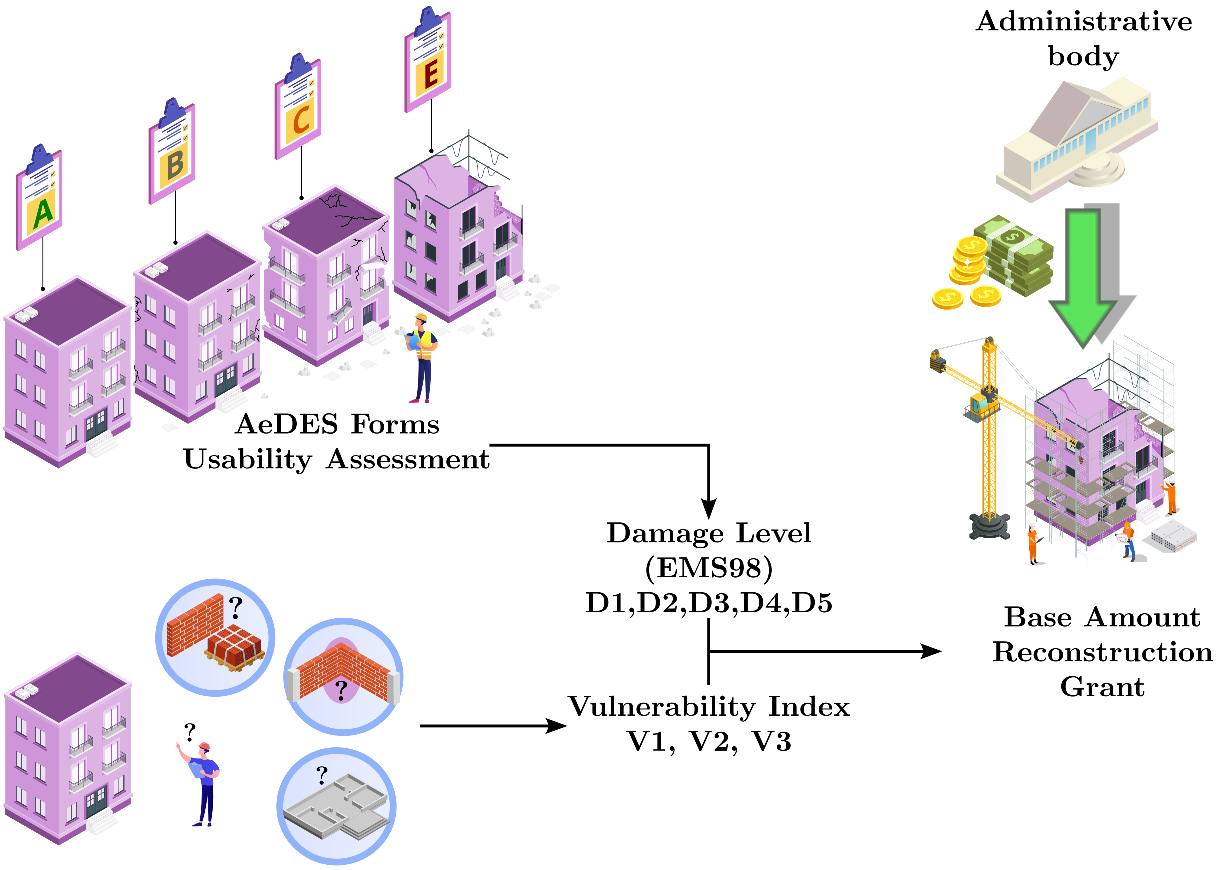

Figure 2: Reconstruction grant base amount definition process [27].

if associated with low, medium, or high vulnerability, respectively. The 9 aspects under consideration and their possible score values are the quality of masonry (0-5-10), quality of orthogonal wall connections (0-1-3), misaligned walls (0-0-2), Spacing of Orthogonal Walls (0-1-2), Roof Vulnerability (0-2-4), Floor Vulnerability (0-3-6), Offset Floors (0-0-4), Non-structural and Secondary Elements (0-1-2), and plan and elevation irregularities (0-2-3). Therefore, the maximum reachable value of the global vulnerability index score can be 36. Its distribution along the herein considered dataset has been depicted in the count bar chart of Fig. 1 (c). The procedure for determining the base amount of the reconstruction grant is schematically illustrated in Fig. 2.

To summarize, the present dataset refers to 2230 masonry buildings belonging to 11 MIC list municipalities. Every instance of the dataset contains 9 features related to each single vulnerability aspect used to compute the global vulnerability index. Another feature column refers to the usability class based on the AeDES survey forms. Additionally, to consider the physics-based information of the input demand from L'Aquila 2009 seismic event, another feature column is the peak ground acceleration (PGA) of every single municipality, computed considering regional attenuation laws for the epicentral distance with the municipality centroid [21]. Another feature is represented by the plan surface of each building. The output column is represented by the base reconstruction authorized grant for every single building instance.

3 RECONSTRUCTION COSTS PREDICTION WITH RANDOM FORESTS

The main goal of this preliminary study is to analyze the potential of using ML models for predictive purposes of the reconstruction cost grant based solely on the vulnerability index.

Since predicting seismic economic losses before an earthquake occurs is often of interest, it is worth underlining that the vulnerability index can be evaluated in advance of a seismic event actually striking. Therefore, the usability scores have not been considered at all in the training phase of the current study. Conversely, the availability of actually observed building usability data represents a special case hardly ever known. Therefore, the availability of this information is an important reference to reliably evaluate the goodness of the ML model predictions of economic losses before an earthquake occurs. The ML task has been set up by subdividing the dataset into four reasonable cost classes. As a first approximation, the analysis herein has been conducted considering a uniformly spaced reconstruction grant spanning 600 euros per square meter, thus identifying four progressively increasing grant classes, as illustrated in the pie chart of Fig. 3. The data distribution evidences a clear unbalance among the classes, with the prevalent part about 61% belonging to the average grant of 600-1200, rather than the tails of the highest grants associated only with 2% of the available data or the lowest grant (about 7%). Despite the authors are aware that this unbalanced scenario is a severe issue for any ML model, the current study has been conducted while still considering these four uniformly spaced cost classes. Indeed, this case could still be of potential interest for any government body from the perspective of administrative simplifications of defining only four equally spaced grant classes.

The dataset has been split into a training and a test set, using the hold-out training-test procedure, with the typical relative proportions of 80%-20%. The adopted multi-class classification ML techniques are Decision trees (DT) [9] and Bagged Trees (BT) [8] with their available implementation in the MATLAB ML toolbox [22]. DT is a supervised learning algorithm based on a divide-and-conquer strategy with greedy search guided by the optimal split points within the tree. BT is a special case of random forests (RF), i.e. an ensemble ML technique that improves classification performance by generating multiple bootstrapped samples of the dataset and training multiple decision trees. The final classification prediction is obtained by majority voting. The adoption of many weak learners is the widely recognized method of ensemble learning, which strengthens the robustness of the learning process against noisy data. To increase the performance of the ML predictors, the ten-fold stratified cross-validation procedure has been adopted [7], and the classification metrics have been averaged among the 10 splits of the training set, and the default hyperparameters provided by the MATLAB ML toolbox [22] have been systematically refined.

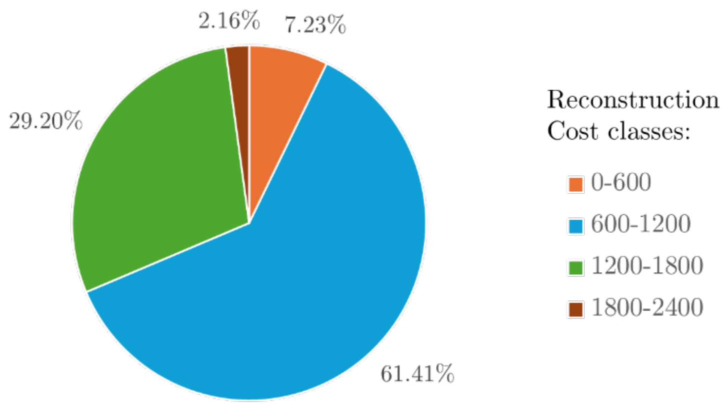

Figure 3: Uniformly-spaced reconstruction cost classes considered in this preliminary study.

4 PRELIMINARY RESULTS AND DISCUSSION

In this section, the results of the hold-out final test procedure are reported, based on the DT and BT with optimized hyperparameters. Several well-known classification metrics have been computed (accuracy, precision, recall, F1-score) [7], including those specialized for handling imbalanced datasets [18], i.e. the balanced accuracy. The model benefits from ensemble learning, reducing overfitting issues. Specifically, DT exhibited the weakest performance, with an accuracy of 80% and a balanced accuracy of only 60%.

However, the BT model also struggled with less-represented categories due to its sensitivity to imbalanced data and the lack of ensemble techniques to mitigate variance. Indeed, it is worth observing that precision and recall metrics are very low for the 1800-2400 euros per square meter class. Anyway, as expected, ensemble methods, like the BT, generally outperform the single DT by aggregating predictions from multiple models and using majority voting.

Considering the averaged balanced accuracy results, the BT model seems to deliver quite satisfying results with a ML model working as a reconstruction cost grant predictive tool based on the sole vulnerability scores. However, based on the current preliminary results, it is worth underlining the current existing limitations, which can be addressed with future in-depth studies. Foremost, the currently adopted reconstruction grant amount subdivision is uniformly spaced, which provides strongly unbalanced classes in terms of the cardinality of each class. In the state-of-the-art literature [5], it is well-acknowledged that the learning process in this kind of situation is strongly limited, since the ML model is more prone to learn the majority class rather than the minority ones. The latter is often of major interest because it focuses on capturing tail behaviors. Therefore, future studies should consider different class separations, in order to attempt to avoid this biased learning phenomenon. Another aspect to account for in the future is the choice of the ML model. Indeed, the ensemble learning is already mitigating the effect of noise in data, avoiding the biased judgment of a single weak learner, such as a single DT. Nonetheless, it would be of interest considering other data-dimensionality strategies, such as principal component analysis (PCA), thus attempting to reduce the number of categorical features under consideration and trying to force the model to learn hidden patterns in data.

Table 1: Performance metrics of selected classification models for predicting the following cost categories: 0-600, 600-1200, 1200-1800 and 1800-2400, considering as input parameters the vulnerability scores, the surface, and PGA as classification features.

Model	Categoriy No.	Euros/m^2	Precision	Recall	F1-score	Accuracy	Balanced Accuracy
DT model	1	0-600	0.53	0.67	0.59	0.90	0.60
	2	600-1200	0.92	0.85	0.88		
	3	1200-1800	0.38	0.55	0.44		
	4	1800-2400	0.13	0.25	0.17		
BT model	1	0-600	0.75	0.87	0.80	0.89	0.80
	2	600-1200	0.96	0.91	0.93		
	3	1200-1800	0.64	0.82	0.72		
	4	1800-2400	0.40	0.60	0.48		

5 CONCLUSIONS

In this study, the authors analyzed reconstruction cost data related to masonry buildings the L'Aquila earthquake event that occurred in Italy in 2009. The process for reconstruction cost grant exact base amount definition has been briefly described, underlining the importance of two important sources of information regarding the structural standpoint. Firstly, the building usability evaluation from rapid post-earthquake forms (AeDES forms) is used to determine five damage classes. On the other hand, the other fundamental data for administrations to determine reconstruction grants is the seismic vulnerability index of the buildings. For the herein considered masonry buildings, vulnerability has been determined with a simplified approach, considering the sum of scores associated with nine structural aspects investigated. Therefore, based on these nine features, the authors attempted to train a ML-assisted predictive tool of the granted reconstruction amount for masonry buildings in 11 municipalities close to L'Aquila city. A Decision Tree and a Random Forest of the type of bagging trees have been adopted with the standard hold-out training test classification procedure. The preliminary results provided by these two ML models demonstrated a possible viable solution for future ML-assisted more sophisticated tools. Indeed, limitations of unbalanced learning and noise in data is currently limiting the actual performance of the herein trained ML models. Moreover, in the future, it could be of actual interest to also introduce the usability data to strengthen the reconstruction grant ML predictions, with a potential evident benefit for administrations for simulating post-earthquake scenarios and timely earmarking resources at a regional scale to prevent such disasters.

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REFERENCES

[1] H. Agha Beigi, T.J. Sullivan, C. Christopoulos, and G.M. Calvi. Factors influencing the repair costs of soft-story rc frame buildings and implications for their seismic retrofit. *Engineering Structures*, 101:233–245, 2015. cited By 28.

[2] David Alexander. An evaluation of medium-term recovery processes after the 6 april 2009 earthquake in l'aquila, central italy. *Environmental Hazards*, 12(1):60–73, 2013.

[3] Angelo Aloisio, Yuri De Santis, Francesco Irti, Dag Pasquale Pasca, Leonardo Scimia, and Massimo Fragiacomo. Machine learning predictions of code-based seismic vulnerability for reinforced concrete and masonry buildings: Insights from a 300-building database. *Engineering Structures*, 301:117295, 2024.

[4] Angelo Aloisio, Marco Martino Rosso, Andrea Matteo De Leo, Massimo Fragiacomo, and Maria Basi. Damage classification after the 2009 l'aquila earthquake using multinomial logistic regression and neural networks. *International Journal of Disaster Risk Reduction*, 96:103959, 2023.

[5] Angelo Aloisio, Marco Martino Rosso, Luca Di Battista, and Giuseppe Quaranta. Machine-learning-aided regional post-seismic usability prediction of buildings: 2016–2017 central italy earthquakes. *Journal of Building Engineering*, 91:109526, 2024.

[6] Jack W Baker. An introduction to probabilistic seismic hazard analysis (psha). *White paper, version*, 1(3), 2008.

[7] Christopher M Bishop and Nasser M Nasrabadi. *Pattern recognition and machine learning*, volume 4. Springer, 2006.

[8] Leo Breiman. Bagging predictors. *Machine learning*, 24:123–140, 1996.

[9] Leo Breiman, Jerome H Friedman, Richard A Olshen, and Charles J Stone. *Classification and regression trees*. CRC press, 1984.

[10] D. Cardone and G. Perrone. Developing fragility curves and loss functions for masonry infill walls. *Earthquake and Structures*, 9(1):257–279, 2015. cited By 145.

[11] C.A. Cornell and H. Krawinkler. Progress and challenges in seismic performance assessment. *PEER Center News*, 3(2):1–3, 2000. cited By 830.

[12] G De Martino, M Di Ludovico, A Prota, C Moroni, G Manfredi, and M Dolce. Empirical damage and actual repair costs on rc private buildings after l'aquila earthquake. In *Proceeding of the 16th World Conference on Earthquake Engineering, Santiago, Chile*, pages 9–13, 2017.

[13] Ciro Del Vecchio, Marco Di Ludovico, Stefano Pampanin, and Andrea Prota. Repair costs of existing rc buildings damaged by the l'aquila earthquake and comparison with fema p-58 predictions. *Earthquake Spectra*, 34(1):237–263, 2018.

[14] Marco Di Ludovico, Andrea Prota, Claudio Moroni, Gaetano Manfredi, and Mauro Dolce. Reconstruction process of damaged residential buildings outside historical centres after the l'aquila earthquake: part ii—"heavy damage" reconstruction. *Bulletin of Earthquake Engineering*, 15:693–729, 2017.

[15] DPC – Dipartimento della Protezione Civile. Relazione di esecuzione delle spese sostenute a valere sul contributo del fondo di solidarietà dell'unione europea (fsue). `www.protezionecivile.gov.it/jcms/it/fondo_ue.wp;jsessionid=44D13930AC5E1A6AF40DB253212DDD66`, 2011. Retrieved December 2018.

[16] FEMA. Seismic performance assessment of buildings-volume 2-implementation guide (fema p-58-2). *Seismic Performance Assessment of Buildings, Volume 1 - Methodology*, 2012. cited By 162.

[17] Juan F Fung, Siamak Sattar, David T Butry, and Steven L McCabe. The total costs of seismic retrofits: State of the art. *Earthquake Spectra*, 37(4):2991–3014, 2021.

[18] Haibo He and Edwardo A Garcia. Learning from imbalanced data. *IEEE Transactions on knowledge and data engineering*, 21(9):1263–1284, 2009.

[19] Nikos D Lagaros, Andreas D Fotis, and Stilianos A Krikos. Assessment of seismic design procedures based on the total cost. *Earthquake engineering & structural dynamics*, 35(11):1381–1401, 2006.

[20] A.B. Liel and G.G. Deierlein. Cost-benefit evaluation of seismic risk mitigation alternatives for older concrete frame buildings. *Earthquake Spectra*, 29(4):1391–1411, 2013. cited By 101.

[21] Luca Malagnini, Aybige Akinci, Kevin Mayeda, Irene Munafo', Robert B Herrmann, and Alessia Mercuri. Characterization of earthquake-induced ground motion from the l'aquila seismic sequence of 2009, italy. *Geophysical Journal International*, 184(1):325–337, 2011.

[22] MathWorks. *Statistics and Machine Learning Toolbox*. The MathWorks, Inc., Natick, Massachusetts, 2023.

[23] Giuseppe Nicodemo, Massimiliano Pittore, Angelo Masi, and Vincenzo Manfredi. Modelling exposure and vulnerability from post-earthquake survey data with risk-oriented taxonomies: Aedes form, gem taxonomy and ems-98 typologies. *International Journal of Disaster Risk Reduction*, 50:101894, 2020.

[24] C.M. Ramirez and E. Miranda. Building-specific loss estimation methods & tools for simplified performance-based earthquake engineering. *Building-specific Loss Estimation Methods & Tools for Simplified Performance-based Earthquake Engineering*, 2009. cited By 163.

[25] K. Sassun, T.J. Sullivan, P. Morandi, and D. Cardone. Characterising the in-plane seismic performance of infill masonry. *Bulletin of the New Zealand Society for Earthquake Engineering*, 49(1):98–115, 2016. cited By 125.

[26] Maria Luísa Sousa and Georgios Tsionis. National seismic risk assessment: an overview and practical guide. *Natural Hazards*, pages 1–34, 2025.

[27] Ufficio Speciale per la Ricostruzione dei Comuni del Cratere. Modello integrato per i comuni del cratere: Allegato tecnico. Technical report, Consiglio Nazionale delle Ricerche, Istituto Per le Tecnologie della Costruzione, Sede di L'Aquila, February 9 2023. Prepared by Carlo Capri, Raffaello Fico, Rosanna Gualtieri, Dario Pecci, Adalberto Sacchini, Andrea Venezi. Each update of this document replaces the previous one. Updates are published on `http://mic.usrc.it/`.