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RAPID EARTHQUAKE LOSS ASSESSMENT FRAMEWORK: RELAR PROJECT AND ITS APPLICATION ON THE DATA SET FROM THE KRALJEVO (SERBIA) EARTHQUAKE IN 2010

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Abstract

Rapid earthquake damage and loss assessment is a critical process for evaluating the immediate impacts of seismic events on infrastructure and populations. It involves the quick analysis of structural damage and economic losses. The goal is to provide timely information to emergency responders, government agencies, and decision-makers, enabling efficient resource allocation and disaster response. Advanced technologies such as machine learning, remote sensing, and real-time data analytics have improved the accuracy and speed of these assessments, helping to mitigate the effects of earthquakes and support recovery efforts. This paper presents the RELAR project, funded by the Science Fund of the Republic of Serbia, which aims to improve earthquake loss assessment and recovery processes. By integrating Machine Learning and Image Recognition, the project accelerates response times and enhances the accuracy of damage estimation and repair cost assessments. Traditional methods often suffer from delays and inaccuracies due to data limitations and lack of flexibility. RELAR offers innovative solutions for providing reliable, timely information, even in the absence of ground motion data. The project's objectives include developing practical ML algorithms, validating assessment models, and establishing proactive risk mitigation strategies. Within the paper, a brief overview of the first results of the framework applied to the case of Kraljevo 2010 earthquake is given, showing the methodology of the approach.

Keywords: RELAR, Earthquake, Resilience, Preparedness, Recovery

1. Introduction

Earthquakes rank among the most destructive natural hazards, causing extensive damage and significant losses. The processes of evaluating damage and losses are often time-consuming and have a profound impact on the recovery and functionality of affected communities. Current earthquake damage assessment methodologies mainly focus on predicting damage states and are categorized as either pre-event (a priori) or post-event (a posteriori) models.

A priori damage estimation involves creating seismic vulnerability models for different building types (BTs) without referencing any specific earthquake. The classification of buildings is based on factors such as construction materials, structural design, building techniques, and other characteristics affecting seismic performance. These methods include analytical, empirical, and hybrid approaches [1]. Analytical approaches, grounded in dynamic simulations and calculations, predict potential building damage using techniques such as capacity spectrum analysis, collapse mechanism evaluation, or full displacement-based modeling. These approaches have been thoroughly investigated in prior studies [2,3]. While analytical methods deliver measurable and reliable accuracy for specific BTs, challenges arise due to the diversity of real-world building inventories, variations between constructed buildings and theoretical designs, and the effects of aging or insufficient maintenance on seismic resilience. Consequently, applying these models to diverse building inventories can lead to less reliable predictions of earthquake-induced losses.

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Empirical methods, on the other hand, estimate the probability of damage states (DS) for each BT based on data from past earthquake events. These outcomes are typically expressed as damage probability matrices or continuous vulnerability curves specific to the data source [4], as discussed in studies like Buratti et al. [5] and Eleftheriadou and Karabinis [6] However, the effectiveness of empirical methods is constrained by the scarcity of reliable local data, particularly in areas with limited recent seismic activity [5]. Additionally, similar to analytical methods, combining data from various regions to develop vulnerability models introduces uncertainties. These arise from potential differences between the BTs used to construct the models and those being assessed for future earthquake damage.

Unlike a priori models, which depend on vulnerability relationships established before an earthquake, a new class of a posteriori damage prediction models is emerging. These models address the limitations of a priori approaches by adapting to local conditions observed after an earthquake. A posteriori vulnerability relationships are derived based on observed damage states (DSs) from a sample of affected buildings, gathered through remote sensing techniques or on-site surveys. Remote sensing employs various methods to observe damage, such as aerial and satellite imagery [7] or synthetic aperture radar data [8]. Modern advancements in damage assessment increasingly leverage machine learning (ML) algorithms combined with image processing techniques, enabling damage detection at both individual building and neighbourhood levels [9]. However, many studies using remote sensing have categorized buildings simply as either damaged or intact, which may not provide the level of detail required for accurate loss assessments. An alternative approach, proposed by Ci and Wang [10], introduced a model using aerial imagery to classify buildings into four distinct damage categories. This method applied convolutional neural networks (CNNs) integrated with ordinal regression to determine the severity of building damage. However, research by Eleftheriadou and Karabinis [6] highlighted a common tendency for remote sensing methods to underestimate damage, underscoring the importance of conducting detailed ground-truth verification after an earthquake. Another challenge with remote sensing is its inability to assess internal structural damage, which limits the precision of damage estimations. This gap further emphasizes the complementary role of on-site inspections in achieving a more comprehensive understanding of post-earthquake damage.

Recent developments in recovery and resilience have introduced significant advancements. For instance, Terzić and Kolozvari [11] developed a fully probabilistic and comprehensive analytical framework to evaluate the post-earthquake functional recovery of buildings. Similarly, Blagojević et al. [12] proposed an innovative demand/supply-based approach that extends the Re-CoDeS framework, incorporating dynamic component interdependencies to more effectively quantify disaster resilience. Despite these advancements, a critical gap remains in both research and practice regarding a key aspect of loss assessment—monetizing losses. Current methodologies either rely on overly simplistic models or are riddled with uncertainties, leading to reduced accuracy and reliability [13] Financial loss translates physical damage into monetary terms by estimating the costs of repair and reconstruction. Earthquake-related economic impacts are generally categorized into two types: (a) direct losses, stemming from damage to physical structures, and (b) indirect losses, resulting from disruptions to economic activities. Simple models for economic loss typically calculate property values multiplied by damage metric. The HAZUS-MH [13] framework estimates losses with three levels of precision: Level 1 provides rough approximations based on national database data, Level 2 offers improved accuracy by incorporating local details and expert judgment, and Level 3 delivers the highest precision, using detailed engineering analyses and customized methodologies tailored to a specific community's conditions. This project focuses on developing a Level 3 approach for assessing direct losses, ensuring a highly accurate and context-specific evaluation of economic impacts.

This paper introduces the RELAR (Rapid Earthquake Loss Assessment and Recovery) framework, a project launched in January 2024. The proposed research presents a universal, rapid earthquake loss assessment framework based on Machine Learning and Image Recognition technologies, offering a more accurate, cost-effective, and user-friendly solution compared to existing methods. RELAR assigns damage-state-specific tags to buildings, calculates total repair costs for an affected building portfolio, and develops a portfolio-level recovery timeline. The paper outlines the main objectives,

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key tasks, and methodology of the framework. Additionally, practical aspects related to its application and implementations are thoroughly discussed.

2. Framework and approach of the RELAR project

The goal of this research initiative is to create a universal, machine learning (ML)-driven rapid earthquake loss assessment framework, which promises improved accuracy and greater ease of implementation compared to current methods. In this context, "loss assessment" involves quantifying and monetizing the repair work necessary for rebuilding a community's building stock. The project focuses on three key research areas: earthquake engineering, machine learning, and construction project management. It utilizes earthquake datasets to develop and validate the proposed assessment models. Results from the project will be shared through published papers and guidelines, aimed at informing decision-makers and relevant stakeholders. Fig. 1 offers a visual overview of the research's conceptual framework.

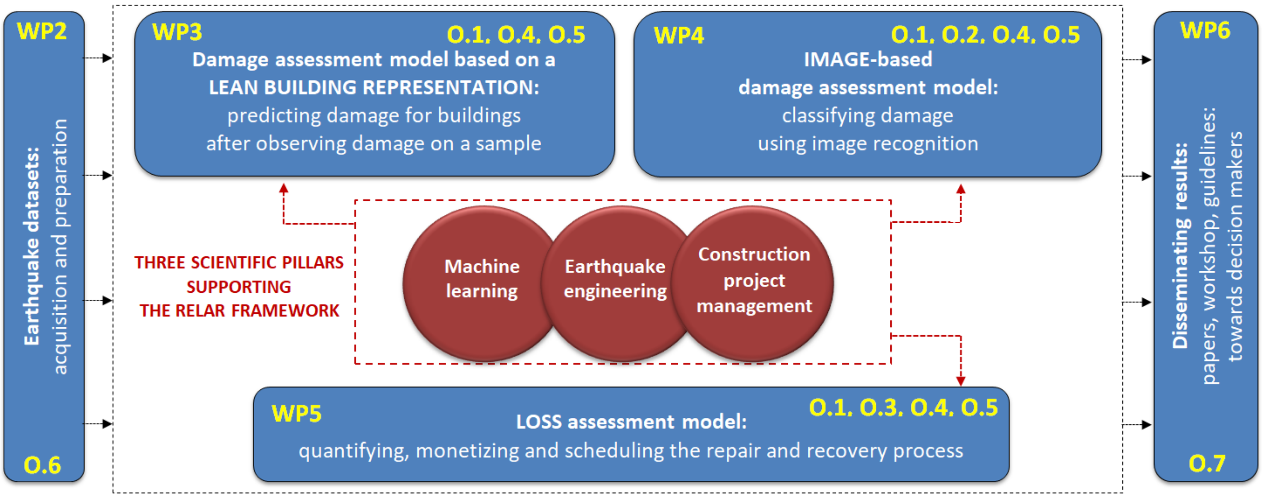

Figure 1. The concept of the project showing work packages (WP), project objectives (O), and scientific research areas supporting the framework

The core component of the proposed framework is a representative set (RS), a carefully selected sample drawn from the local building stock and prepared in advance of an earthquake (Fig. 2). Each building in the portfolio is defined by key characteristics that are linked to potential damage, such as building type or floor count. Immediately after an earthquake, the RS is surveyed to assess the extent of damage. Universal machine learning techniques, including image recognition, are then used to train a local damage assessment model (DAM) based on the RS. This trained model is subsequently applied to predict the damage across the entire building portfolio. Next, a loss assessment model (LAM) uses the damage labels—detailing both the severity and extent of damage—to estimate repair costs and recovery timelines. The proposed sampling strategy, building characterization, and machine learning techniques are designed to be adaptable to any earthquake and region. However, the RS and the DAM are specific to the earthquake in question, ensuring high accuracy in predictions and a swift assessment process using easily accessible resources. A key innovation in this approach is treating an earthquake as a post-event spatial probability distribution of damage, independent of specific ground motion data or building type classifications. This novel methodology is referred to as "Buildings are damage sensors," emphasizing the intrinsic seismic damage information embedded within the buildings themselves.

The proposed implementation protocol for loss assessment is structured into two phases: the pre-earthquake phase and the co-earthquake phase. The pre-earthquake phase begins with the creation of a database derived from raw portfolio data. This step involves defining local building types and

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adopting a streamlined building representation (LBR) that includes easily accessible, damage-related features (such as geographic coordinates, building type (BT), construction year, footprint area, and number of floors), without relying on earthquake-specific data. A representative set (RS) is formed from the portfolio database through a sampling algorithm, with the number of buildings selected as an input parameter. A balance between speed and precision arises in this stage: a larger RS increases observation time but improves accuracy, whereas a smaller RS shortens observation time but may reduce accuracy. In addition to the LBR and sampling algorithm, the universal damage assessment method incorporates an image-based damage assessment model (DAM) that is pre-trained on images of buildings damaged in past earthquakes. A training procedure for developing the local LBR-based DAM is also outlined. The loss assessment model (LAM) is developed during the pre-earthquake phase, utilizing local usage rates and unit costs to estimate repair expenses for various local building types. This comprehensive methodology sets the stage for an efficient and precise earthquake loss assessment process.

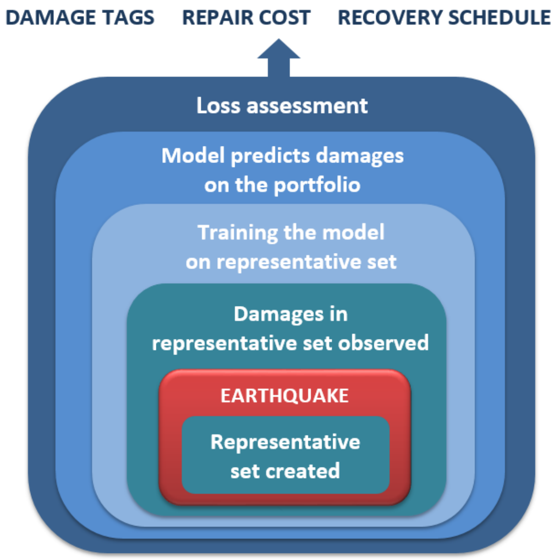

Figure 2. The implementation sequence of the main framework steps

The post-earthquake phase, referred to as the co-earthquake phase, involves the immediate assessment of damage on the representative set (RS). The RS is divided into two segments: expert and non-expert parts. Experts conduct field surveys, capturing photos and assigning damage labels, while non-experts are responsible for taking photos only. The labeled images from experts are then used to update the pre-trained image-based damage assessment model (DAM). This updated model is subsequently used to label the non-expert segment of the RS. Once the RS is fully labeled, it is used to train the lean building representation (LBR)-based DAM. Upon completion of training, the DAM generates damage labels for the entire building portfolio.

The output of the DAM, excluding the green-yellow-red safety tags, is then sent to the loss assessment model (LAM). The safety tags play a critical role in post-earthquake safety measures, with green indicating full access, yellow signaling restricted access, and red marking no access. The LAM, which incorporates damage states (DS), damage extent (DE), and community-specific resource limitations (such as the number of available experts and non-experts, funding, design company availability, licensing speed, and the capacity for rebuilding), predicts the expected repair costs and generates a recovery schedule for the entire portfolio, considering resource constraints. The duration of the co-earthquake phase depends on the resources available within the community and the recovery goals, balancing speed and accuracy. Although this phase typically lasts several days, it is considered rapid. To highlight the framework's adaptability to any region or earthquake, it is important to distinguish between universal and local components. Elements such as the LBR, sampling algorithm,

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pre-trained image-based DAM, the training process for the LBR-based DAM, and the loss assessment procedure are universally applicable to any region and any magnitude of earthquake. The universal approach facilitates the creation of a local RS and locally trained damage and loss assessment models based on damage observed on the RS ("Buildings are damage sensors"). The framework's implementation is both swift and accurate, providing actionable predictions for decision-makers.

The framework operates with basic, readily accessible resources, requiring only a standard computer and an internet connection for storing the portfolio database, training models, and collecting assessor observations in the pre-earthquake phase. During the co-earthquake phase, it relies on a combination of experts and non-experts to assess damage on the RS.

After an earthquake, the proposed framework employs several machine learning (ML)-based classifiers to process each building in a portfolio. These classifiers take a features vector (b) and geo-coordinates (x, y) as input and generate different probability distributions related to damage assessment.

The research plan involves assessing the effectiveness of various classification techniques for each task and across different representative set (RS) sizes. Common classification methods such as ensemble techniques (Random Forest, XGBoost), Neural Networks, and Support Vector Machines will be evaluated. The study will also investigate combining expert-generated labels with those produced by image-based classifiers, aiming to reduce dependence on expert-created labels. This strategy allows for larger RSs to be evaluated quickly by increasing the number of non-expert assessors, ultimately leading to more accurate machine learning-based classification models and, as a result, more precise loss assessments. To determine the most informative representation of a building for each classification task (LBR), various feature selection techniques will be applied to the available datasets. These techniques include univariate methods like Mutual Information, multivariate approaches such as mRMR, wrapper methods that choose features based on their impact on classification performance, and techniques for ranking feature importance in tree-based models. However, it is essential that the selected LBR for each classification task remains easy to acquire and universally accessible.

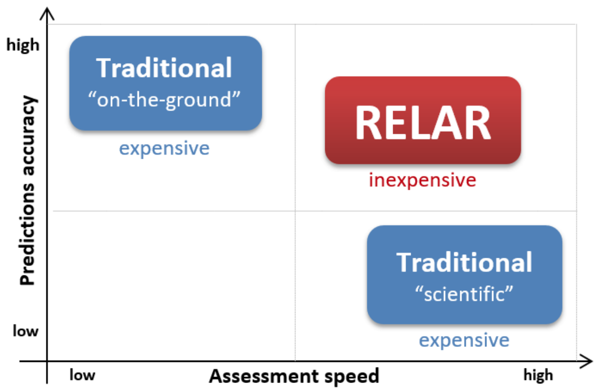

Figure 3. Framework ambition - comparing to other approaches

3. Aim and originality

The proposed framework aims to outperform existing loss assessment methods in terms of speed, accuracy, and cost-efficiency. Traditional "on-the-ground" methods are slow, as they require a detailed inspection of the entire portfolio, and their costs rise significantly due to the time-consuming field surveys conducted by experts. In contrast, the conventional "scientific" approach suffers from inaccuracies due to assumptions and uncertainties, often requiring an expensive network of ground motion sensors. The RELAR framework sets itself apart by being faster than the "on-the-ground" approach, as it relies solely on remote sensing data, and more accurate than the "scientific" approach, as it treats buildings themselves as sensors. This advantage is illustrated in Fig. 3. To achieve these

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goals, the proposed models are aligned with the primary objectives outlined in work packages (WP3, WP4, and WP5).

The upcoming damage assessment model is designed to be trained using observed damage in a representative set of buildings. Its goal is to learn the distribution P(D | b, x, y), which utilizes simplified building features and spatial coordinates. A key innovation of this model is that it does not rely on ground motion data at the specific location of a building, an approach we refer to as "Buildings as damage sensors." As a result, the model can be applied universally across different communities, even in areas without ground motion stations. Additionally, our proposed methodology removes the need for information about previous earthquakes, a ground-breaking feature that distinguishes our approach from existing analytical or empirical methods in seismic damage assessment.

Beyond its independence from ground motion data, the proposed method also departs from the need for buildings (BTs) to fit into predefined categories. Instead, it requires only consistent local-specific building types to be assigned within the affected community. Machine learning-based damage assessment models can effectively understand the seismic behaviour of these locally specific building types based on observed damage in remote sensing (RS) data. This flexibility is particularly significant, as most existing analytical or empirical methods assume rigid building type classifications, which may not align with local construction practices. By accommodating local variations in building types, our approach increases both the applicability and accuracy of seismic assessments in diverse settings.

When two buildings share the same damage state, differences in the damage levels of specific elements, such as walls, may require different amounts of resources for repair. Traditional rapid loss assessment systems often overlook this detail, focusing primarily on damage states without accounting for the variability within specific building elements when estimating monetary losses. As discussed in the Methodology section, our Damage Assessment Model (DAM) is designed to predict the likelihood of various structural and non-structural building elements being at different damage levels (low, medium, high). This prediction is made using a simplified set of building features and spatial coordinates (LBR). By quantifying the damage levels for each building element individually, our approach enhances the precision of repair cost estimations. This leads to a more accurate, resource-constrained recovery schedule at the portfolio level, offering a stronger framework for recovery planning.

To accurately measure the extent of damage, it is crucial to express the required repair quantities as ratios relative to building elements. These ratios represent the percentages of various repair tasks associated with different damage states. Converting qualitative Damage Extent (DE) categories (low, medium, high) into these ratios involves a survey process. Experts with experience in post-earthquake field inspections will complete tables that assign percentages for different repair works based on specific Building Type/Damage State (BT/DS) combinations. The collected data will then be harmonized to ensure consistency. This innovative approach improves the accuracy of loss assessments by providing more precise monetization and ensuring the transferability of the methodology.

By following this process, we can achieve greater accuracy compared to traditional methods that estimate costs per footprint area. Additionally, this system allows for regular updates to the cost matrix, either by adjusting unit prices or by applying local unit prices in different markets. This flexibility ensures that the loss assessment remains relevant and accurate over time, making it adaptable to various regions and evolving conditions.

4. Anticipated effects

The RELAR framework, with its enhanced speed and accuracy, plays a vital role in helping communities manage the aftermath of earthquakes. It supports local and governmental agencies in making informed decisions throughout the recovery phase. By providing immediate, color-coded tags

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(green-yellow-red) right after an earthquake, it improves life safety and facilitates more reliable and precise compensation. This accelerates both functional and social recovery, enabling quicker returns to work, reducing psychological stress, and organizing community events.

Local authorities can use the recovery schedule and resource availability to plan the recovery process efficiently, while government agencies receive a clear estimate of total repair costs soon after the earthquake. The framework also contributes to improving the quality of life by reducing the economic impact of prolonged recovery periods and promoting sustainable economic growth. Furthermore, the proposed framework is particularly beneficial for developing countries and municipalities without extensive ground motion sensor networks, offering an accessible and adaptable solution to earthquake damage assessment.

The successful implementation of the RELAR project has significant potential for advancing various community and societal goals. It introduces an innovative, universally applicable approach to rapid earthquake loss assessment, setting the stage for new research avenues and methodologies in the field.

Municipalities and regions that implement the RELAR framework stand to benefit economically through faster access to accurate data, enabling more informed decision-making. This improves the allocation of funds and financial resources, minimizing wasteful or ineffective spending. The framework's capacity to provide precise quantification and monetization of repair needs fosters collaboration among designers, contractors, and material suppliers, supporting coordinated efforts to rebuild damaged structures. Additionally, quantifying demolished buildings contributes to planning for the recycling and reuse of construction materials, aligning with circular economy principles and benefiting the environment.

Insurance companies will also gain from the RELAR framework by offering better insurance policies to individuals, businesses, and industries, enhancing their competitiveness with more diversified products. The results of the project encourage cross-sector collaborations between associations and companies, extending beyond the core project team and Serbia, and aligning with the European Neighbourhood Regional Policy. Maintaining the project website after its completion will ensure ongoing communication between the scientific community, disaster risk management professionals, insurance providers, and policymakers, increasing the project's visibility and impact. Furthermore, the project’s broader influence includes promoting social and economic cohesion, especially by facilitating the transfer of technology to regions with less advanced infrastructures.

5. Framework application on 2010 Kraljevo, Serbia earthquake dataset

A brief overview of the Framework application on 2010 Kraljevo, Serbia earthquake dataset is here given, with more details presented in [4,14,15].

A rapid earthquake loss assessment framework is introduced, leveraging a machine learning damage classification model combined with a representative sampling algorithm. Using a Random Forest classification approach, the model predicts damage probability distributions, which are then integrated with an expert-curated repair cost matrix. This enables the estimation of expected repair costs for individual buildings and the calculation of direct losses across the affected region. Unlike traditional methods, the proposed framework avoids using explicit earthquake and soil type data. Instead, such factors are inherently represented within the spatial damage distribution. To capture this distribution effectively, a sampling algorithm based on K-means clustering identifies a minimal set of buildings that reflect the seismic risk profile of the area, independent of future seismic events. The model is iteratively refined with each damage observation cycle, progressively improving the precision of the loss assessments.

The M5.4 earthquake that struck Kraljevo, Serbia, in 2010 serves as a representative example of a modern earthquake disaster. This event resulted in 2 fatalities and slightly over 100 injuries requiring medical attention. However, it caused significant structural damage, with nearly 6,000 buildings affected, a quarter of which were deemed unsafe for habitation. Damage inspection and assessment were carried out over several weeks by structural engineers from Kraljevo and other Serbian cities.

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Unfortunately, the collected data on damage and recovery efforts were not centralized, with some records existing only in paper format. Additionally, many damage survey entries were incomplete and could not be utilized. Information on undamaged structures was sourced from the property tax assessor's office of Kraljevo. The finalized dataset comprises 1,979 buildings, of which 652, located in three key districts of the city, experienced damage during the earthquake. The spatial distribution of these buildings and their respective damage states is illustrated in Fig. 4.

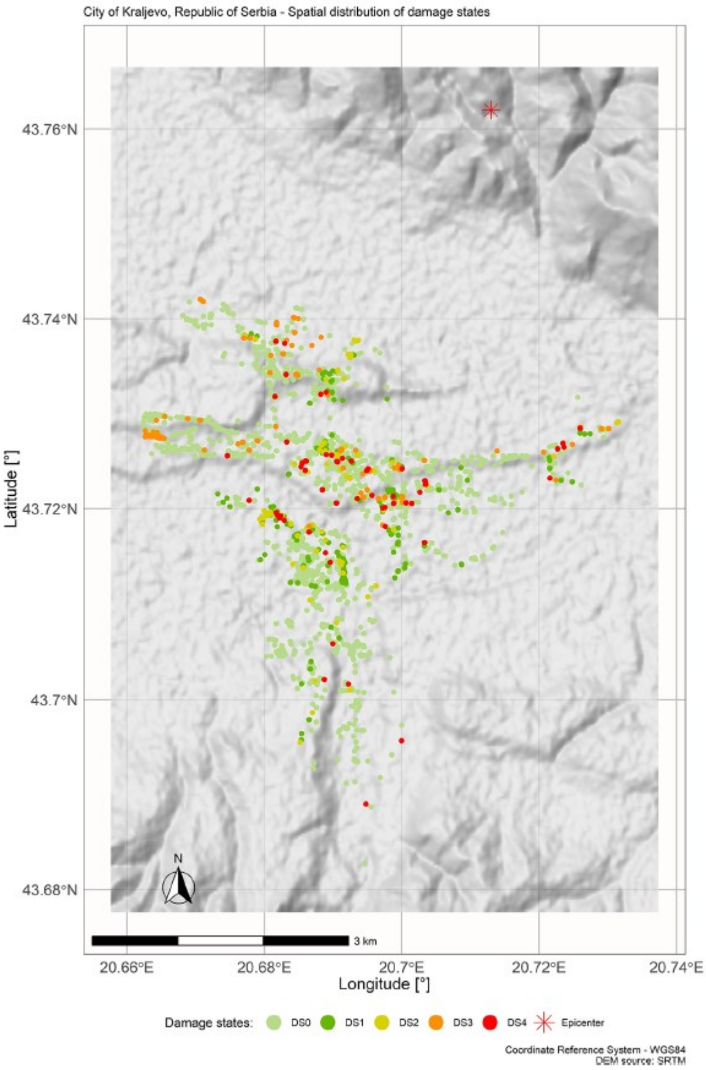

Figure 4. Spatial distribution of database buildings and their damage states after the 2010 Kraljevo earthquake [4]

First an evaluation of the model's performance on two fronts: the accuracy of predicted Damage States (DSs) and the accuracy of Predicted Repair Costs (PRCs), based on an expert-defined repair cost matrix. To validate the model, a square confusion matrix N for k distinct DSs (classes) was constructed iteratively across 10 cross-validation folds. Each element nij in N represents the number of buildings with an actual DSi classified as DSj.

The results, presented in Table 1, demonstrate a high accuracy rate of 85% for the random forest classification model. Precision and recall metrics for DS0 indicate the model's ability to effectively identify undamaged buildings, which constituted the majority class. DS1 and DS3 classifications were moderately accurate, while DS2 and DS4 presented challenges due to the limited number of buildings in these categories within the training set (127 in DS2 and 64 in DS4). This scarcity of data in certain

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DSs significantly impacted the model's classification performance. Increasing the representation of these underrepresented damage classes would likely enhance the model's overall performance.

Table 1. Confusion matrix with accuracy, precision, and recall measures [4]

Actual	Predicted						
	DS0	DS1	DS2	DS3	DS4	Total number of buildings	Recall
DS0	1314	11	0	1	1	1327	0.99
DS1	27	234	38	18	11	328	0.71
DS2	6	64	37	13	7	127	0.29
DS3	7	31	17	69	9	133	0.52
DS4	3	18	14	10	19	64	0.30
Total	1357	358	106	111	47	Accuracy 1673/1979 = 0.85	
Precision	0.97	0.65	0.35	0.62	0.40		

DS: damage state.

To develop the repair cost assessment model, a matrix detailing repair costs for all combinations of Damage States (DS) and Building Types (BT) is essential. Table 2 displays the calculated mean repair costs per unit building footprint area for the dataset of buildings affected by the 2010 Kraljevo earthquake. A statistical analysis of the actual repair costs (ARCs) paid by the Government of Serbia was conducted for all BTs in DS1 and DS2. These ARCs only covered material costs, as homeowners performed the repairs themselves. The resulting cost intervals were broad—approximately 20% of the mean value—highlighting the variability in repairs for buildings with less severe damage.

For DS3, repair scenario analyses were conducted, encompassing both labor and material costs. Due to the engagement of various design and construction firms to plan and execute repairs following the earthquake, a wide range of repair methods was developed for each BT. The scenario analyses revealed significant variation in repair costs per unit footprint area, resulting in wide cost intervals for DS3 as well. The values presented in Table 2 reflect the mean costs of the most frequently used repair methods for each BT, providing a standardized basis for the repair cost assessment model.

Buildings classified as DS4 were demolished and subsequently rebuilt. To estimate the DS4 values presented in Table 2, the costs of reconstructing comparable buildings damaged in recent disasters across Serbia were analyzed. In most instances, the Government of Serbia supplied prefabricated wooden-frame houses as permanent replacements for the destroyed structures. The average cost of constructing this type of building in Serbia is approximately €350 per square meter of gross building area, which is roughly equivalent to the building's footprint area multiplied by the number of floors.

Table 2. Mean repair cost matrix (€/m^2) [4]

	BT1	BT2	BT3	BT4	BT5	BT6
DS1	3.43	12.04	8.36	10.43	9.14	9.14
DS2	13.40	16.04	15.14	18.86	17.54	18.64
DS3	55.69	46.30	44.15	38.87	29.72	32.75
DS4	350.00	350.00	350.00	350.00	350.00	350.00

BT: building type; DS: damage state.

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The subsequent step involved validating the repair cost assessment model. For this purpose, the predicted repair costs (PRCs) for all buildings in the dataset were computed using two distinct approaches: a soft rule and a hard rule. The soft rule incorporates a probability distribution for damage states (DSs), allowing for a weighted calculation of repair costs based on the likelihood of each DS. In contrast, the hard rule utilizes only the most probable DS for each building to determine its repair costs, providing a deterministic estimate.

The total actual repair costs (ARC) paid by the Serbian government were significantly lower than what would have been required for the complete recovery of all damaged buildings due to financial constraints. For buildings in DS1 and DS2, the government covered only the cost of materials, while the homeowners bore the expenses for design (if applicable) and labor. For DS3 buildings, the government funded the repair design, necessary materials, and a nominal amount for labor costs. In the case of DS4 buildings, the government fully financed the construction of replacement houses. The predicted repair costs (PRC) calculated using the soft rule (Equation 1) and the hard rule (Equation 2) were €2,822,640 and €2,160,123, respectively. The relative error, expressed as |PRC – ARC|/ARC, was approximately 20% for the hard rule but reduced to only 5% for the soft rule. This result highlights the advantage of using damage probability distributions (soft rule) over discrete DS labels (hard rule) for repair cost assessment, as it significantly improves accuracy.

The proposed framework was applied to the 2010 Kraljevo earthquake dataset, which included 1,979 buildings, six building types (BTs), and five damage states (DSs). The predicted total repair costs were highly accurate, with a relative error of less than 20%, even after rapidly inspecting only 10% of the building portfolio. This task, which would take the Civil Protection system in Kraljevo approximately two days to complete, demonstrated the framework's efficiency.

Although the framework does not depend on seismological networks, it does require the initial setup and ongoing updates of the building portfolio database, the repair cost matrix, and the training of a local damage assessor network. If these tasks can be implemented in communities exposed to earthquake risks, the framework offers a practical and sustainable solution to improve earthquake risk mitigation and recovery efforts.

6. Conclusions

This paper provides an overview of the necessity and current state of earthquake loss assessment methods, with a particular focus on the RELAR (Rapid Earthquake Loss Assessment and Recovery) project. It offers an in-depth look at the three-year project's goals, plans, and steps to achieve its objectives.

The RELAR project, which will span three years, will involve a team of 10 experts from fields such as earthquake engineering, machine learning, mathematics, big data, construction management, and programming. Alongside publishing the project's results in academic journals and presenting at conferences, the outcomes will also be shared via platforms like Instagram, YouTube, and the project's website. Two sets of guidelines will be developed: one from WP4, which will focus on recommendations for capturing high-quality images with various cameras to optimize spatial information for the image-based Damage Assessment Model (DAM), and the other from WP6, detailing the implementation of the RELAR framework in earthquake-prone communities. These guidelines will cover the necessary resources, algorithms, and procedures for utilizing the DAM and Loss Assessment Model (LAM) in both pre- and co-earthquake phases.

At the project's conclusion, a workshop titled "Rapid Earthquake Loss Assessment for Resilient Societies" will be held at GRFUB to present the key findings and distribute project materials. This workshop will feature lectures from the project team and external collaborators, including simulations and practical demonstrations of case studies. It will target students, engineers, practitioners in the insurance and construction industries, as well as representatives from local municipalities and experts in law and economics.

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The RELAR project has just begun, and with its detailed plan and well-defined tasks, it promises to be an exciting and impactful journey. The project's ultimate aim is to develop a framework for rapid loss assessment after earthquakes, contributing to society and improving the post-disaster situation for local populations affected by future earthquakes.

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