Article

Development of a Fuzzy Inference System Based Rapid Visual Screening Method for Seismic Assessment of Buildings Presented on a Case Study of URM Buildings

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Abstract: Many conventional rapid visual screening (RVS) methods for the seismic assessment of existing structures have been designed over the past three decades, tailored to site-specific building features. The objective of implementing RVS is to identify the buildings most susceptible to earthquake-induced damage. RVS methods are utilized to classify buildings according to their risk level to prioritize the buildings at high seismic risk. The conventional RVS methods are employed to determine the damage after an earthquake or to make safety assessments in order to predict the damage that may occur in a building before an impending earthquake. Due to the subjectivity of the screener based on visual examination, previous research has shown that these conventional methods can lead to vagueness and uncertainty. Additionally, because RVS methods were found to be conservative and to be partially accurate, as well as the fact that some expert opinion based developed RVS techniques do not have the capability of further enhancement, it was recommended that RVS methods be developed. Therefore, this paper discusses a fuzzy logic based RVS method development to produce an accurate building features responsive examination method for unreinforced masonry (URM) structures, as well as a way of revising existing RVS methods. In this context, RVS parameters are used in a fuzzy-inference system hierarchical computational pattern to develop the RVS method. The fuzzy inference system based RVS method was developed considering post-earthquake building screening data of 40 URM structures located in Albania following the earthquake in 2019 as a case study. In addition, FEMA P-154, a conventional RVS method, was employed to screen considered buildings to comparatively demonstrate the efficiency of the developed RVS method in this study. The findings of the study revealed that the proposed method with an accuracy of 67.5% strongly outperformed the conventional RVS method by 42.5%.

Keywords: earthquake; seismic assessment; rapid visual screening; fuzzy logic; unreinforced masonry

1. Introduction

Determination of existing buildings’ seismic vulnerability is one of the challenging issues of civil engineering. Especially in European urban areas, there are many unreinforced masonry (URM) buildings that were constructed before the development of design codes as illustrated in Figure 1. Because these buildings were constructed and/or designed prior to the development of design codes, they are vulnerable to an impending earthquake. Additionally, the chaotic growth of urban areas has led to a lack of consideration of seismic design standards as well as to poor construction. Therefore, special attention should be paid to existing buildings in order to prevent potential losses. Existing buildings are generally used as residential buildings without any evaluation and/or improvement in their structural system [1]. In order to determine damages that may take place in existing buildings during a major earthquake, a large-scale seismic assessment should be employed. Nevertheless, a building seismic assessment is carried out by employing three level seismic vulnerability assessment methodologies–rapid visual screening (RVS),
preliminary vulnerability assessment (PVA), and detailed vulnerability assessment (DVA)—
that range from simple to complicated, respectively. RVS methods require less time in terms
of the time necessary to assess each building. In this context, vulnerability assessment of
existing buildings could be performed by using RVS methods, which are deployed for the
large-scale seismic assessment of many buildings.

Because damage to a single building during an earthquake causes a significant loss of
energy, it is necessary to perform a pre-earthquake building assessment for a sustainable
urban environment in terms of social, economic, and environmental aspects. Additionally,
determining the resilience of existing buildings, as well as new buildings, against an
impending destructive earthquake and taking the necessary measures could enhance the
sustainability of the urban environment. Therefore, it is vital to have an accurate RVS
method for a pre-earthquake building assessment.

An experienced screener could visually examine existing buildings by conducting an
RVS method known as a “sidewalk survey”. During implementation of the selected ap-
proach, site-specific building characteristics (such as building type, site seismicity, soil type,
irregularities, and so on), that affect building seismic performance, are considered by using
linguistic parameters (e.g., Low, Moderate, High). Many methods, such as the USA—FEMA
P154 [3], Italy—GNDT [4], Greece—OASP [5], Turkey—EMPI [6] and RBTE-2019 [7], New
Zealand—NZSEE [8], Canada—NRC [9], European—RISK-UE Project [10] and EMS-98
Scale [11], as well as others, were employed in previous investigations. Furthermore, RVS
methods have been developed and/or implemented for particular building types, such
as health facilities [12–15]; school buildings by the State Organization of Schools Reno-

Figure 1. Categorization of existing European buildings in terms of employment of seismic design
code (Compiled based on [2]).
vation of Iran (SOSRI) [16], the SAARC Disaster Management Center (SDMC) [17], and churches [18–21]. In addition to the RVS methods established nationally or institutionally, there has been extensive research carried out on the development [22–24], implementation [25–31], enhancement [1,32,33], and review [34–36] of conventional RVS methods. Because the parameters that each of these RVS methods takes into account vary and because they were developed based on site-specific building characteristics, it is difficult to compare these RVS methods [36]. Additionally, even though traditional RVS methods have undergone extensive research and are widely accepted, these techniques have demonstrated limited accuracy in terms of one-to-one building damage state classification [37]. Additionally, it has been discovered that these methods show higher building vulnerability than that of the real one [34,38–40]. Furthermore, since some conventional RVS methods, such as NRC [9], were developed based on expert opinion rather than analytical evaluations, they are hard to modify. While conventional RVS methods require less time for a building assessment, previous research in literature [36,38,41–43] has indicated that uncertainty and vagueness could appear during the conventional visual inspection of buildings because of the subjectivity of the screener during the implementation of these methods. On the other hand, fuzzy logic-based RVS, which is a probabilistic method, could consider uncertainty and vagueness within its framework. Availability of each parameter has graded between 0 (no existence) and 1 (full existence), resulting in more consistent results [44]. To explicitly classify vulnerable buildings without a detailed investigation, Dritsos and Moseley [45] recommended developing a novel RVS approach with the employment of fuzzy logic. As a result, it was advised that RVS methods be developed that can be modified based on newly collected data and technological advancements. These RVS methods can be developed as either an improved version of the current conventional RVS methods or as unique methods. In order to validate developed RVS methods, data should be gathered by inspecting the buildings after an earthquake and/or applying DVA methods on existing buildings. For the development of RVS methods, different artificial intelligence algorithms are used, including fuzzy logic [46–48], machine learning [49–52], neural networks [53,54], and hybrid models [55–58]. Some of the first fuzzy logic-based RVS techniques were devised by Tesfamariam and Saatcioglu [59,60], Şen [61], and Moseley and Dritsos [62]. Tesfamariam and Saatcioglu developed risk-based seismic assessment systems to assess the vulnerability of reinforced concrete buildings employing fuzzy logic algorithms [59,60]; they stated that the developed vulnerability assessment systems show a good correlation with the post-earthquake building screening data gathered after the 2003 Bingöl and the 1994 Northridge earthquakes. Furthermore, a fuzzy logic-based RVS method was developed and implemented in Istanbul, Turkey by Şen; however, unlike the previously summarized studies [59,60], this method was not validated using post-earthquake or DVA-based data [61]. A fuzzy logic-based RVS method for reinforced concrete buildings was developed by Moseley and Dritsos using post-earthquake building screening data that was gathered following the Athens earthquake in 1999 [62]. The findings showed that, in terms of identifying the state of building damage, the developed method was at least as effective as traditional RVS methods. Additionally, it was noted that the proposed method could be improved by utilizing further optimizable capabilities of fuzzy logic. 

In contrast to the majority of the fuzzy logic-based RVS methods developed for RC structures (De Iuliis et al. [63], Tesfamariam and Saatcioglu [59,60,64], Elwood and Corotis [65], Harirchian and Lahmer [37]), there are very few studies on developing fuzzy logic-based RVS methods for steel (Shahriar et al. [47]) and URM (Parameswaran et al. [66], Mazumder et al. [67]) buildings. Additionally, the existing fuzzy logic-based RVS methods established for URM buildings were not validated by being compared with post-earthquake screening and/or DVA-based building data [66,67]. Furthermore, according to Dritsos and Moseley, there is still room for RVS method development in terms of damage state classification precision [45,62]. Additionally, the methods used to develop fuzzy logic-based
RVS methods for engineering buildings can also be used to develop RVS for roads [68], bridges [69], railways [70], etc.

To this end, this study developed a new fuzzy logic-based RVS method for URM buildings and, in contrast to existing methods developed for URM buildings, demonstrated the accuracy of the developed method by comparing its findings with post-earthquake screening data collected after the earthquake in Albania in 2019. The collected post-earthquake data of URM buildings from the 2019 Albania earthquake were utilized in a fuzzy inference system (FIS) to determine the building damage state. The pre-earthquake assessment of existing URM buildings was performed in this study by using the FEMA P-154 RVS method, as a representative of conventional RVS methods accepted as highly advanced, to demonstrate the efficiency of the developed RVS method. The findings support the idea of the need to develop a more accurate RVS method based on FIS, showing 67.5% accuracy compared to the conventional RVS method (FEMA P-154), which has shown an accuracy of 25%. Whereas the conventional RVS method misclassifies structures three times out of four, the developed RVS method accurately classifies buildings with a success rate of about three times out of four.

2. Study Area and Building Stock

Albania is located in the southeastern part of Europe, on the western side of the Balkan Peninsula. It is positioned in the Mediterranean, between the Adriatic and the Ionian Seas, and has suffered from severe earthquakes after 1900 (such as 1905—Shkodër—Ms: 6.6, 1911—Ohrid lake—Ms: 6.7, 1920—Tepelenë—Ms: 6.4, 1926—Durres Ms: 6.2, 1930—Llogara Mountain—Ms: 6.3, 1959—Lushnjë—Ms: 6.4, 1960—Korcë—Ms: 6.5, 1962—Fier—Ms: 6.0, 1967—Dibër—Ms: 6.6, 1979—Montenegro—Ms: 6.9) [71–73]. Earthquakes are the most significant category of natural hazards in Albania [74]. On November 26, 2019, two earthquakes with magnitudes of 6.4 and 5.4 on the Richter scale struck Albania. The earthquake had a modified Mercalli intensity of VIII (Severe). Figure 2 depicts the 6.4 Richter scale earthquake epicenter location on a map with a black star within a red indicator. A black star in a white indicator is used to identify the station location where the ground motion data is recorded on the map. Additionally, a red indicator on the map designates the location of the Tirana city center. An earthquake with a peak ground acceleration value of approximately 0.12 g in the horizontal direction was recorded near Tirana, Albania, according to accelerogram records; in other words, a 6.4 Richter scale earthquake. The earthquake had an impact on a number of Albanian municipalities, including Durrës, Tirana, Shijak, Kamëz, Krujë, Kurbin, Kavajë, and Lezhë. The average shear wave velocity ($V_{s30}$) was 312 m/s where the Tirana earthquake data are recorded [75]. The corresponding soil category of the station was C in terms of Eurocode 8 [76] classification, and III based on KTP-N.2-89 [77]. Furthermore, according to the KTP-N.2-89 [77], the seismicity at the site was classified as Intensity VII [78,79].

Masonry structures are the most common building type in Albania because unreinforced masonry was used to build both public and residential structures during the communist era (from 1944 to 1990) [80,81]. Structures built before 1993 were damaged during the 2019 earthquake at a rate of 24%, whereas structures built after 1993 were damaged at a rate of 10% [82]. The data utilized for the post-earthquake building survey consist of unreinforced masonry structures damaged in Tirana as a result of the 2019 earthquake. The information was gathered by a team dispatched by the Hungarian government, which included the third author. The post-earthquake building screening data were collected by visually inspecting each building from the outside and, if possible, from the inside. The masonry structures in Tirana consist of reinforced concrete floors and some of them consist of columns erected at re-entrant corners, as illustrated in Figure 3. Buildings were classified into three damage states during the post-earthquake screening: low, moderate, and high. The post-earthquake building screening data considered here contain 40 URM buildings: 25 designated with low-, nine with moderate-, and six with high-damage states.
The 2019 Albania earthquake epicenter, station, and the location of the examined buildings (Tirana).

Sample masonry buildings collected during the post-earthquake screening: (a) URM building with corner columns, (b) URM building with rigid floor, (c) URM building with an indistinguishable floor type from the outside.

3. The Relationship between the Parameters and the Damage State

By establishing a link between input parameters and the output parameter, RVS techniques are utilized to categorize buildings according to their safety levels (damage state). In comparison to more comprehensive assessment methods, RVS methods have the advantage of being able to develop this link in a relatively short time period. The link between input parameters (vertical and plan irregularity, construction quality, and structural system) and the output parameter (damage states of the considered post-earthquake screening data) is illustrated in Figure 4.
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Based on the considered parameters, the number of buildings is divided into two classes for plan and vertical irregularity, and three classes for construction quality and structural systems. Buildings in yes and no categories for vertical and plan irregularity are rated based on their damage states as illustrated in Figure 4. Although most buildings are observed to be classified as low damage in both the yes and no categories for vertical and plan irregularity, there is no direct correlation between building damage states and irregularities. The findings from comparing the building damage state and construction quality did not reveal that there is a direct correlation between the percentages of buildings assigned to each class and the increase or reduction in building construction quality. A structural system of a building has a considerable impact on the seismic safety levels of the buildings. The degree of damage in stand-alone buildings is significantly lower than that in row buildings. Furthermore, the degree of damage in row-end buildings is lower than that in middle-row buildings.

There is no direct relationship found between vertical irregularity, plan irregularity, construction quality, and structural system as input parameters and the damage state. As a result, a link between these input parameters and the damage state needed to be established. Therefore, a FIS-based RVS method, which is a strong approach for determining buildings’ damage states, was developed in this study to establish the link between the input parameters and the damage state.

4. Fuzzy Logic-Based RVS Method Development

In this section, the stages from the development of the fuzzy logic-based RVS method to its implementation are explained in line with the purpose of the study. The relevant sub-headings for the section are shown in Figure 5.
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Figure 5. Organization of the fuzzy logic-based RVS method development.

4.1. Development of FIS-Based RVS Method Framework

Fuzzy logic was primarily used in earthquake engineering throughout the 1970s while attempting to assess seismic risk [83]. Later, it was applied to RVS methods in various researches [37,41,64,84] by employing the linguistic variable processing functionality of fuzzy logic. In this study, post-earthquake building inspection data of URM buildings from the 2019 Albania earthquake were used to develop a fuzzy logic-based RVS method.

Multiple input parameters (vertical irregularity, plan irregularity, construction quality, and so forth) based on fuzzy aggregation-oriented RVS provide damage state prediction as a single output value. The performance index is computed by using the scoring system, approximate equations, and empirical data utilized in conventional RVS techniques; however, the FIS establishes a link between numerical and symbolic models by processing the contained vagueness [85]. The fuzzy sets consider uncertainty by taking into account the individual parameters’ values in the interval [0, 1]. The fact that linguistic inputs and outputs (low, moderate, etc.) have different meanings for different people, and the results are obtained with the collaboration of more than one expert, causes the data to be noisy and the system to contain uncertainties. This uncertainty is considered in the FIS [86]. The FIS-based RVS scheme developed to determine individual building damage state is shown in Figure 6.

The applicability of the fuzzy logic-based RVS method can be demonstrated by using post-earthquake building screening data collected following a severe earthquake. The general steps of implementing a FIS-based RVS are as follows.

- Identify variables and corresponding parameters,
- Collect and process building post-earthquake screening data,
- Define hierarchical parameters relation as shown in Figure 6,
- To fuzzify variables define each individual membership function,
- Define rule formation system operation and inference implication,
- Define defuzzification to transform fuzzified values to a crisp output,
- Perform sensitivity analysis.
Explanations of steps 1 through 6 for the development of the fuzzy logic-based RVS method are not included in this study; these are detailed in [88].

4.2. Determining RVS Parameters

RVS techniques are developed by considering numerous input parameters that could influence structural seismic behavior. In our method, the vulnerability of existing buildings is determined by applying fuzzy logic-based RVS to a large number of buildings and taking into account the variety of building characteristic parameters. The considered input parameters for developing the FIS-based RVS method are vertical irregularity, plan irregularity, construction quality, year of construction, structural system and site seismic hazard analysis. In this context, the presented fuzzy logic-based method’s damage prediction sensitivity could be determined by considering the post-earthquake building screening data collected after the 2019 Albania earthquake. Accordingly, Figure 7 illustrates the percentages of each relevant input parameter in the considered data as a pie chart.

Figure 6. FIS-based RVS flowchart (compiled by authors based on [87]).

Figure 7. Distribution of the linguistically classified parameters.
The corresponding explanations involved in determining the parameters considered for a FIS-based RVS technique developed in this investigation are provided below, one by one. Furthermore, additional in-depth explanations of these parameters can be found in the authors’ earlier study [88] in addition to the ones provided below.

The structural plan with re-entrant corners has plan forms such as E, L, T, U, +, and so forth classified as plan irregularity. Structures with plan irregularities are labeled Yes, whereas buildings without plan irregularities are labeled No. The plan irregularity rates of the building data are depicted as Yes and No in Figure 7a.

Vertical irregularity characteristics include buildings on a steep slope, weak floors, soft floors, high wall opening amounts, differences in story heights, and in-plane and out-of-plane setbacks. Buildings are classified as Yes if they have vertical irregularities; otherwise, they are classified as No. Figure 7b illustrates the vertical irregularity percentages of the building data utilized in this investigation as Yes and No.

The current state of the seismic capability of existing buildings is evaluated by taking into consideration the deterioration of the material qualities of structural elements. The degradation of the material used, foundation settlement, and cracks in the walls affect the seismic performance of masonry structures. All the above-mentioned factors are considered to classify the construction quality. Subsequently, the construction quality of a building is classified qualitatively as Poor, Moderate, or Good [87,89]. Figure 7c illustrates the Poor, Moderate, and Good construction quality proportions based on the building data used in this study.

The year of construction (YC) relates to the building’s age, which shows both the construction quality and the design technique used for that particular structure. Buildings are categorized into three distinct groups based on the historical evolution of seismic design codes in Albania [90], as presented in Table 1: Low Code, Moderate Code, and High Code. Based on the historical evolution of the Albania seismic design code, the thresholds for the categorization of the year of construction have been determined.

<table>
<thead>
<tr>
<th>Year of Construction (YC)</th>
<th>Low Code (LC)</th>
<th>Moderate Code (MC)</th>
<th>High Code (HC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>−0.01 × YC + 20.27</td>
<td>−0.03 × YC + 59.8</td>
<td>0.1</td>
</tr>
</tbody>
</table>

According to the development stages of Albanian standards, a structure with an unknown construction year is presumed to have been built before 1942 (Low Code), as was similarly considered by Tesfamariam [87].

Whether URM buildings are constructed in a row or stand-alone has an impact on the building’s seismic resistance. Therefore, three URM building types have been defined to account for the impact of the structural system on the building damage state: Standalone, Row End, and Row Middle. In addition, the ratios of these variables in the data are presented in Figure 7d. The transformation of linguistic variables representing structural system categories such as Standalone, Row Middle, and Row End to crisp values is illustrated in Section 4.4.

An acceleration response spectrum was utilized in this study, which was derived using earthquake time-history acceleration data recorded in the Tirana, Albania, station in 2019. The dominant period of each building was then evaluated using the determined building height. The approximate fundamental structural period ($T_a$) of URM buildings was estimated by employing Equation (1), as defined in ASCE/SEI [91].

$$T_a = C_1 \times h_n^{3/4}$$

where, $C_1$ is the coefficient of the building period and is defined as 0.05 for URM buildings. The approximate building height ($h_n$) was determined by multiplying the average story
height \((h_{\text{avg}})\) by the number of floors \((n)\) shown in Figure 7c. In this study, \(h_{\text{avg}}\) for URM buildings is considered as 2.8 m as defined in the literature [75,92].

The Site seismic hazard (SSH) is based on building height (number of stories), site seismicity and site condition (soil type). An Acceleration response spectrum was used to determine the spectral acceleration \((S_a)\) values corresponding to the predicted dominant natural vibration periods of buildings as illustrated in Figure 8. The ground motion data used to generate the response spectrum in Figure 8 were chosen from the Tirana station, which is nearest to the examined buildings. The computed \(S_a\) values depicted in Figure 8 with red dots for the SSH analysis module were then integrated into the hierarchical FIS system-based RVS method through the use of the appropriate fuzzy clusters.

![Figure 8. Site-specific acceleration response spectrum and building height-based corresponding spectral acceleration values.](image)

Building damageability was determined using the hierarchical system presented in Figure 6 by integrating the site seismic hazard module with building vulnerability as the outcome parameter of the building vulnerability module. Building damageability is classified into different damage states, which are classified as very low, low, moderate, high, and very high based on the assigned intervals. The building damageability index based on the CanRisk [93] damage levels is used to convert the output into linguistic parameters. By merging None and Light into Low and Heavy and At/Near Collapse into High, the number of damage levels was decreased from five to three. The final scores obtained from the development fuzzy logic-based RVS method could be converted to linguistic variables based on the classification information provided in Table 2 to represent building safety levels linguistically.

<table>
<thead>
<tr>
<th>Building Damageability</th>
<th>Low 0–0.4</th>
<th>Moderate 0.4–0.6</th>
<th>High 0.6–1.0</th>
</tr>
</thead>
</table>

Table 2. Building damage states intervals (compiled based on [93]).

As a result, each parameter discussed under this title is extensively explained in another paper the authors have written [88].

4.3. Fuzzy Logic Theory, Fuzzy Inferences

Fuzzy logic was initially developed by Zadeh [94] in 1965 as an approximate reasoning approach that considers fuzzy sets. Fuzzy sets are special sets where the elements’ truth values can be not only 0 or 1 but any quantity between them (certainly, including 0 and 1). Traditional set operators (e.g., union, intersection, or complement) are applicable between fuzzy sets, although each operator can be implemented by many functions, according to the axioms that apply to them. Non-specificity occurs as a result of unspecified parameters.
Disagreement about the selection of a parameter leads to conflict (discord). Uncertainty consists of ambiguity and vagueness. Vagueness occurs when there is not a strict distinction opportunity to select a parameter. Ambiguity is represented by conflict (discord) and non-specificity [87]. Fuzzy logic is used to take into account vagueness and uncertainty along with many parameters.

Fuzzy modeling mainly consists of fuzzy sets and logical connections represented by fuzzy set operators between them. Fuzzy inference systems (FISs) are the fundamental decision-making components of the fuzzy logic systems (FLSs). A FIS establishes interconnection between the crisp (non-fuzzy) inputs and crisp output(s). The process of a FIS can be divided into three steps: input processing (fuzzification), fuzzy inference (rules), and output processing (defuzzification), as illustrated in Figure 9.

![Figure 9. Fuzzy logic system.](image)

To consider both linguistic and/or numeric input variables, the fuzzification phase of the input processing is activated. The numerical input parameters are assigned to the fuzzy sets representing linguistic antecedent parameters of the FIS. The FIS’s IF-THEN rules employ the IF [antecedents] and THEN [consequents] conditional expressions at the stage of the fuzzy inference engine, based on the relevant reasoning algorithms. The AND connections are implemented as fuzzy intersections and the ORs as fuzzy unions. The integrity of the fuzzy model can be ensured by considering all potential values of the input parameters while establishing a significant set of rules [39,61,95].

Membership functions (MFs) express a degree of truth in fuzzy logic. Such MFs (e.g., triangular with green lines, trapezoidal with blue lines), as shown in Figure 10, are utilized to transform quantitative measures into qualitative descriptions for the implementation of the FIS [41,96]. By assigning the determined MF to certain particles, the crisp input values are transformed into a homogeneous scale to implement fuzzification as an input processing based on the granulation [59,97]. In a fuzzy set, 0 represents non-membership, 1 represents full membership, and a value in the [0, 1] interval is defined as partial membership to express the vagueness of the parameters. By using the fuzzy logic methodology, qualitative judgment can be integrated with numerical reasoning as a descriptive (linguistic) judgment. In this context, the fuzzification and defuzzification stages that process the qualitative judgment are of great importance in the application of fuzzy logic [64], based on approximate reasoning algorithms to handle uncertainties [59].

![Figure 10. Triangular and trapezoidal fuzzy membership functions.](image)
The fuzzy inference engine is a fuzzy logic reasoning process comprised of rules and inference, and uses fuzzy vectors to map output fuzzy sets. The term rules in fuzzy inference engines refers to a decision-maker’s assessment of opinions in a particular environment with uncertainties [59]. The most used techniques of the fuzzy inference methods are the Sugeno [98] and Mamdani [99] ones. Because the Mamdani fuzzy inference method is intuitive, widely accepted, and works well with human input [100], a Mamdani type fuzzy model was utilized in this study.

The output processor of the FLS contains a defuzzifier. The defuzzification, which is the last stage of the FLS to make a decision, refers to the step of converting qualitative fuzzy outputs into quantifiable crisp outputs [41,59,64,101]. Many defuzzification methodologies (e.g., center of gravity, center of area, mean of maxima) are suggested to produce crisp outputs [59,64,96,102].

### 4.4. Sensitivity Assessment of Developed RVS Method

Building features are linguistically identified during a rapid visual screening based on the seismic surveys of buildings. In order to use the collected data in the established FIS-based RVS framework, these definitions need to be converted into suitable numerical values [87]. Therefore, sensitivity analysis was performed to investigate how changes in transformation values affect the outputs (damage state) in the RVS method. After defining the input parameters and corresponding intervals of the sub-classification parameters, such as whether vertical irregularity exists or not, optimization techniques were used to obtain the optimum possible transformation values. The values for the transformations that were acquired as an outcome of the optimization are illustrated in Table 3.

<table>
<thead>
<tr>
<th>Vertical Irregularity</th>
<th>Plan Irregularity</th>
<th>Construction Quality</th>
<th>Structural System</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>0.13</td>
<td>0.80</td>
<td>0.13</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Additionally, it should be highlighted that there are other possible transformation values that can influence how well the system matches the designated damage states from a post-earthquake screening. Nevertheless, accuracy of the system has been altered in this investigation by performing the transformation values given in Table 3.

Furthermore, according to the study conducted by Mogharreban and DiLalla [103], the findings achieved by employing the system developed as a consequence of applying various defuzzification techniques have been altered. Nevertheless, when the defuzzification method is selected for the developed system, the range of the results (damage state indexes between 0 and 1) needs to be considered. Therefore, different defuzzification methods (centroid, bisector, mean of maxima, smallest maxima, and largest maxima) were performed in the developed RVS system. It was found that the largest maxima defuzzification method represents the building damage index better in the range of 0 to 1.

### 4.5. FIS-Based RVS Implementation

A fuzzy inference system (FIS)-based RVS method was used to determine building damageability by taking the membership functions and rules that have been defined into account to provide a relationship between inputs and outputs, as illustrated in Figure 9. First, the linguistic input parameters were transformed to numerical values ranging from 0 to 1, as detailed under the heading 4.4. Sensitivity Assessment. The FIS was then executed. To calculate output variables by employing the FIS, 61 fuzzy rules are defined in this investigation. The fuzzy logic-based RVS methodology was implemented by employing Python [104] programming language. The Python programming language’s fuzzy logic package SciKit-Fuzzy (skfuzzy) was utilized to execute a RVS based on the FIS. The NumPy library, available in the Python programming language, was used to perform scientific com-
putations. Furthermore, the Pandas library was employed for data analysis. The Matplotlib library in Python was used to visualize the data and results.

Building damage states are determined using a hierarchical framework, as depicted in Figure 6. There are antecedents and consequents to each stage. Because of the computational hierarchy, a parameter that is consequent in the initial stage may become antecedent in the subsequent stage. In addition, the complexity and computational burden of the model are reduced as a result of the developing hierarchical system.

The values obtained by employing the FIS-based RVS technique should be related to the assigned post-earthquake building damage states. Therefore, structures identified as having higher damage states should obtain higher scores, whereas structures identified as having low damage states should be identified with lower scores. The corresponding intervals are given in Table 2. On the other hand, the accuracy of the method necessitates overlapping the post-earthquake damage states with the predicted damage states. The validity of the proposed method relies on the fulfillment of the aforementioned criteria [46]. Finally, buildings could be categorized based on their intervention priority and the indicated damage states. Additionally, the findings were compared with the FEMA RVS approach-based implementation results, which are described below, to show the validity of the developed method as an alternative to the conventional one.

5. FEMA P-154-Based RVS

The FEMA RVS technique was initially used for a pre-earthquake assessment of existing buildings in 1988. It was revised in 2002 and 2015, as was further detailed in the previous study [36]. In this study, to implement the FEMA RVS method, 40 URM buildings in Tirana, Albania, were considered. As a consequence of the evaluation conducted following the catastrophic earthquake that occurred in Albania in 2019, these 40 structures were categorized into three seismic damage states: Low, Moderate, and High.

In order to apply the FEMA RVS method, the seismicity of the site needs to be determined. Therefore, the $S_s$ and $S_1$ values need to be evaluated. $S_s \,(\text{short} - \text{period, or } 0.2 \,\text{s})$ and $S_1 \,(\text{short} - \text{period, or } 1.0 \,\text{s})$ spectral acceleration response values are required in this study to calculate the ASCE design spectrum for Tirana, Albania. Therefore, Equations (2) and (3), which were derived by Lubkowski and Aluisi [105], were employed to calculate $S_s$ and $S_1$ values.

\[ S_s / \text{PGA} = 0.3184 \,\text{PGA} + 2.1786 \]  
\[ S_1 / \text{PGA} = 0.5776 \,\text{PGA} + 0.5967 \]  

where the peak ground acceleration (PGA) is referred to as the highest value of the acceleration time history data resulting from an earthquake at a particular location on the ground.

Correspondingly, the site-specific acceleration response spectrum generated for the 2019 Albania earthquake, as well as the ASCE [106] design acceleration response spectrum, drawn based on the determined $S_s$ and $S_1$ values, are illustrated in Figure 11. The site-specific response spectrum and the design response spectrum are well correlated.

The spectral acceleration values derived for 0.2 and 1 s periods were compared to the intervals given in Table 2-2 of FEMA P-154, respectively. The comparison of the derived values from the design and site-specific response spectra led to the conclusion that the seismicity of the site is moderate. The compatibility of these earthquake data-based site-specific response spectra with the design response spectra indicates that the chosen screening form fits well with the seismicity of the site. Street photographs of the buildings from 2016 were then acquired using Google Earth software in order to perform a FEMA P-154 moderate pre-earthquake screening form.
The damage state and severity of damage that may occur in a building during an earthquake varies depending on the building type. Therefore, a schematic representation of the damage that may emerge corresponding to the building damage states for masonry buildings is illustrated in Figure 12.

Buildings are classified as safe or suspicious based on their final score (FS) values determined by using FEMA P-154. Therefore, FS values need to be reprocessed in order to identify building damage states for comparison with FIS-based RVS and post-earthquake damage states. Nevertheless, Nanda and Majhi [107] present the categorization given in Table 4 to classify the FS values acquired as a consequence of the building evaluation.

**Figure 11.** ASCE design spectra vs. response spectra in Tirana (TIR1 Station).

**Figure 12.** EMS-98 [11] based damage state definitions of masonry buildings.
pursuant to FEMA P-154 [3] as building damage states based on EMS-98 [11], which is illustrated in Figure 12.

Table 4. Relationship between damage potential and the FEMA P-154 final score (Compiled based on [107]).

<table>
<thead>
<tr>
<th>RVS Final Score</th>
<th>High Probability Damage Grade</th>
<th>Damage Potential Very High Probability Damage Grade</th>
</tr>
</thead>
<tbody>
<tr>
<td>FS &lt; 0.3</td>
<td>5</td>
<td>or 4</td>
</tr>
<tr>
<td>0.3 &lt; FS &lt; 0.7</td>
<td>4</td>
<td>or 3</td>
</tr>
<tr>
<td>0.7 &lt; FS &lt; 2.0</td>
<td>3</td>
<td>or 2</td>
</tr>
<tr>
<td>2.0 &lt; FS &lt; 2.5</td>
<td>2</td>
<td>or 1</td>
</tr>
<tr>
<td>FS &gt; 2.5</td>
<td>Probability of Grade 1 damage</td>
<td></td>
</tr>
</tbody>
</table>

6. Results

The results of this study are thoroughly explained under this heading. The Section 6 presents the results obtained from the application of the conventional RVS method, the newly developed RVS method, the comparison of the results obtained from the application of these methods, and ends by providing a screening form for building data collection, as shown in Figure 13.

![Figure 13. The flowchart describing the presentation of the result.](image)

6.1. The Conventional RVS Results

Building damage states were determined using the FEMA P-154 RVS technique and the FIS-based RVS model developed in this study. To illustrate the accuracy and applicability of the techniques, the determined building damage states need to be compared to post-earthquake screening data collected after the 2019 Albania earthquake in Tirana.

The examined structures were classified as a result of the reassessment of the final score values assigned to each building using the FEMA method in accordance with the classification introduced in Section 6.3.3. Damage classification based on the FEMA showed:

- Damage state of eight buildings is high probability of Grade 5 and very high probability of Grade 4.
- Damage state of one building is high probability of Grade 4 and very high probability of Grade 3.
- The other remaining 31 buildings are in the high probability of Grade 3 and very high probability of Grade 2 damage state.

Figure 14 depicts the damage states determined employing FEMA P-154, which may be compared to the post-earthquake damage states. The determined damage states and
post-earthquake damage states are illustrated as green x and red + in Figure 14, respectively. The x-axis in Figure 14 illustrates the building indexes, and the y-axis depicts building damage states as Low—0, Moderate—1, and High—2. The damage states of 17 buildings were categorized as High while the damage states of 23 buildings were classified as Moderate in accordance with the FEMA-based assessment. However, a comparison of damage states derived using the FEMA technique with post-earthquake damage states shows that the FEMA-based calculations are 25% accurate in terms of a one-to-one building damage state match.

Figure 14. Building damage state classification based on FEMA P-154 and post-earthquake screening data.

6.2. The Developed RVS Results

The damage states identified during post-earthquake building screening need to be compared with the fuzzy logic-based determined damage states to demonstrate the applicability of the FIS-based developed RVS method. Building damage states via post-earthquake screening and the FIS-based RVS method are illustrated in Figure 15. The x-axis and y-axis of the figure illustrate buildings’ indexes and damage states, respectively. The FIS-based determined damage states are illustrated with green x and post-earthquake damage states are illustrated with red + in Figure 15. Classification by employing the developed RVS method shows that 27 buildings are classified as having Low damage states, 11 buildings are assigned Moderate damage states, and two buildings’ damage states are categorized as High. The damage states derived using the FIS-based RVS technique is 67.5% accurate in terms of damage states’ one-to-one overlapping when compared to the post-earthquake damage states.

Figure 15. Developed RVS method-based building screening comparison with post-earthquake screening data.
6.3. Comparison of RVS Results

A comprehensive comparison of RVS methods with post-earthquake data is necessary to verify the accuracy of RVS methods in terms of buildings’ damage states determination capabilities. Finally, accuracy of the assigned building damage states is determined by how far or near they are to the collected damage states. The accuracy of the RVS methods is determined using a variety of methods explained below:

I. The number of buildings allocated to each of the damage states is compared.
II. The accuracy is measured using one-to-one matched damage states with post-earthquake data shown in the diagonal cells of confusion matrices (CMs).
III. To determine accuracy, the number of buildings classified as one class more severe and one-to-one matching damage states is considered.
IV. Accuracy is determined by the number of structures designated as one class minor and one-to-one matching damage states.

6.3.1. Comparison of Damage State Percentages

Figure 16a depicts percentages of building damage states based on a post-earthquake screening. According to post-earthquake inspections, 65% of structures are classified to be in the Low damage state, 20% are in the Moderate damage state, and 15% are in the High damage state. The damage states determined by application of the developed FIS-based RVS method are shown in Figure 16b and the FEMA P-154 screening method-based building damage state classification is depicted in Figure 16c. The developed FIS-based RVS method categorized 67.5% of the structures as Low, 27.5% as Moderate, and 5% as High. However, FEMA-based screening results show that 57.5% of structures have Moderate damage and 42.5% have High damage.

![Figure 16. Building damage states based on post-earthquake screening, FIS and FEMA P-154: (a) post-earthquake damage states; (b) FIS-based damage states; (c) FEMA-based damage states.](image)

6.3.2. One-to-One Comparison of Damage States

Another illustration technique named the confusion matrix (CM) is used to assess and illustrate the effectiveness of the model. CMs are plotted as shown in Figure 17 to illustrate the relationship between true labels and determined labels for FIS-based developed RVS and the FEMA RVS method. The CMs of the FEMA and the RVS methods are shown in Figure 17a,b, respectively. The proportion of the label defined on the vertical axis that is computed correctly is shown in diagonal CM cells when the damage state labels on both the horizontal and vertical axes coincide. The percentages in the other cells in each row indicate that the true label of the corresponding row was incorrectly categorized. While FEMA shows 67% accuracy rate for damage state High, FIS was able to accurately identify one of the six buildings (≈17% accuracy). FEMA’s accuracy in determining building damage statuses of nine moderately damaged structures is 75%; however, the FIS-based RVS technique is 62.5% accurate. Furthermore, although the FEMA RVS did not categorize any of the 25 buildings as Low, the FIS-based RVS correctly classified the structures’ damage
states as Low with an ≈80.77% accuracy. Consequently, the building examination based on the FEMA RVS technique accurately identified 25% of buildings, but the developed FIS-based RVS greatly surpasses the conventional method by correctly classifying 67.5% of the buildings.

6.3.3. Comparison of One Class More Severe Damage State Classifications

To determine accuracy, the number of buildings classified as one class more severe and one-to-one matching damage states is considered, as illustrated in the following table. The conventional RVS method classifies 17 buildings as one class more severe than their damage states, whereas the developed RVS method defines the damage state of four buildings as one class more severe, as illustrated in Table 5. Additionally, the developed RVS method and the conventional RVS method accurately identified the one-to-one building damage states of 27 and 10 buildings, respectively. As a result, the developed RVS method based on FIS provides better results in determining the actual damage state. The FEMA RVS approach, on the other hand, has categorized the buildings as more vulnerable to earthquakes than they actually are.

Table 5. Comparison of the developed RVS method with the conventional RVS method on a one-to-one and a one-class more severe damage state basis.

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIS based RVS method</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-to-one</td>
<td>21</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>One more severe</td>
<td>4</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>FEMA RVS method</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-to-one</td>
<td>0</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>One more severe</td>
<td>15</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

6.3.4. Comparison of One Class Minor Severe Damage State Classifications

Accuracy is determined by the number of structures designated as one class minor and one-to-one matching damage states, as shown below. The developed RVS method defined the damage states of five buildings as one class less severe. In contrast, the conventional RVS method defined the damage states of two buildings as one class less severe, as shown in Table 6. Although two buildings were categorized in a lower vulnerability class than the real one using the FEMA RVS method, the FIS-based RVS method classified five buildings in a lower vulnerability class than the actual one.
Table 6. One-to-one and one-class minor severe damage state classification comparison of the developed RVS method with the conventional RVS method.

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIS-based RVS method</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-to-one</td>
<td>21</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>One less severe</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>FEMA RVS method</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-to-one</td>
<td>0</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>One less severe</td>
<td>0</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, the results obtained utilizing the developed RVS method employing the FIS algorithm allow for more accurate damage states to be classified. The classification of buildings based on their safety level, as well as the None and At/Near Collapse intervals, was considered to make use of more accurate classification potential. The authors discovered that no building was in the collapse damage state after assessing the post-earthquake screening image data based on the EMS-98 [11] damage state classification explanation in Figure 12. The FIS-based RVS approach has verified the research findings by classifying none of the buildings’ damage state index within the [0.9, 1.0] interval. Furthermore, as a consequence of the post-earthquake assessment, the damage states of the buildings were categorized as at least Low, indicating that these buildings should not be in the None damage state band. In addition, the comparison by considering the None damage state index range of [0.0 to 0.2] revealed that none of the buildings’ damage states is designated as None.

6.4. RVS Form for the Developed RVS Method

In order to use the developed RVS method, it is necessary to create a screening form for data collection. Figure 18 depicts a general implementation screening form for collecting data using the developed RVS method. The top left sections of the form required general information about the site, screener, and building. The screener can provide additional comments about the inspected building in the top right section. Photos and/or drawings are required to visualize the building plan and vertical configuration. The building height could then be assessed based on the number of stories and average story height, as well as the exact building height assigned. The corresponding acceleration response spectrum is defined based on the site seismicity and soil properties to evaluate the structural spectral acceleration value corresponding to the fundamental structural period. Furthermore, the URM buildings’ structural systems could be chosen as alone, row middle, or row end. Construction quality, plan irregularity, and vertical irregularity are all rated from 0 to 1. As an example, if the construction quality is very poor, the value is 0; and if the construction quality is very good, the value is 1.
7. Discussion

In this study, to determine the building damage states, the FEMA P-154 RVS method as a representative method of conventional RVS methods and the developed FIS-based RVS method were employed. Google Earth software was used to perform pre-earthquake visual inspections of structures in order to implement the FEMA P-154 RVS technique. Building images from 2016 were collected from the software. The collected building information is based on the building’s facade, and the knowledge of the buildings’ occupants. In this approach, the FEMA RVS screening forms were used to examine 40 URM buildings.
from the outside. The determined building damage categories were compared with the post-earthquake building screening data from the 2019 Albania earthquake.

Furthermore, to compare findings with FEMA damage states and post-earthquake data, the None and the Collapse indexes of the FIS-based RVS method were considered within the Low and High damage states, respectively. If the FS score is greater than 2.5, the building’s damage state is classified as the probability of grade 1 damage which means negligible to slight damage, as illustrated in Figure 12.

In contrast to the many developed RVS techniques, this study demonstrates the accuracy of RVS techniques by comparing the determined damage states with post-earthquake building screening data collected after the 2019 Albania earthquake. This research provides a FIS-based RVS approach and demonstrates the accuracy of the FEMA RVS method for pre-earthquake screening of URM buildings. Based on the one-to-one comparison of the damage states of both methods, the developed FIS-based RVS method (67.5% accuracy) has made significant advances over the conventional RVS method (25% accuracy). In this manner, Figure 17 shows that the RVS method developed by using FIS is more convenient than the conventional RVS method. The method established for the rapid visual screening of URM buildings in this study has a higher accuracy rate (67.5%) than the devised method by Harirchian and Lahmer [37] for reinforced concrete buildings (62.2%).

The FIS-based RVS method can be utilized to differentiate and illustrate structures that are classified as None or At/Near Collapse based on the corresponding damage state intervals. The range [0–0.2] is classified as None by CanRisk [93], whereas the range [0.8–1.0] is described as At/Near Collapse. When the None damage index range is considered in the FIS-based RVS method, no building was classified as being in the None damage index range as in the post-earthquake data. This demonstrates that the RVS technique based on FIS is not underestimating the safety levels of the buildings. The range of [0.8–1.0] covers the At/Near Collapse damage states, whereas the range of collapse [0.9–1.0] for distinguishing buildings with higher (collapse) damage is considered in this study. Moreover, when the Collapse damage index range is considered, no building’s index falls within this range. This indicates that the RVS model based on FIS does not overestimate damage states. Besides, the examination of the images captured during the post-earthquake screening period reveals that the structures under consideration in this study are not in the Collapse damage state.

The findings of the FIS-based developed RVS technique implementation demonstrate that even though the buildings are classified as Low damage state, it should not be disregarded. Taking necessary precautions to prevent and/or mitigate the damage that may occur as a result of an impending earthquake is essential.

The FIS-based RVS technique was constructed employing six input parameters in this research. Furthermore, the existing method may be modified and/or improved by using the various RVS methods’ parameters that are comparatively illustrated by Bektaş and Kegyes-Brassai [36]. The presented FIS-based methodology could be adopted worldwide by implementing proper adjustments and/or additions to the parameters under consideration based on building stock information. Modifications to the input parameters should be performed based on the seismic characteristics of the considered area and the building attributes. The quantity and attributes of the parameters, including the associated allocated fuzzy sets and linguistic variables, could all be modified. The proposed approach could be used to examine existing buildings and additionally to categorize them depending on the precautions that need to be observed, such as renovation or retrofitting.

8. Conclusions

Existing building safety levels should be determined prior to an impending earthquake in order to reduce potentially hazardous consequences. Since RVS methods are easy and computationally efficient, they could be employed to assess the existing building stock. Therefore, it is essential to have an accurate RVS method to classify buildings before an impending earthquake. However, the FEMA RVS method, which is used in this study to evaluate buildings and is regarded as a good indicator of conventional RVS methods,
revealed that the results have a limited degree of accuracy. Additionally, the vagueness and uncertainties that could arise with the use of conventional RVS methods need to be eliminated within the developed RVS method. The main accomplishment of this study is the demonstration of the conventional RVS technique’s accuracy and the development and implementation of a new FIS-based RVS method for URM buildings based on post-earthquake building screening data from the 2019 Albania earthquake. In contrast to existing fuzzy logic-based RVS methods, which are developed for URM buildings, this study validated the accuracy of the developed RVS method by comparing results to post-earthquake screening data. Furthermore, because the developed method incorporates fuzzy logic theory into its architecture, it could be easily further enhanced and/or applied to another location.

Comprehensive sequential development and implementation of the FIS-based RVS technique is presented. The applicability of the proposed RVS method has been verified by comparing the determined damage states with FEMA P-154, and the post-earthquake building screening data. Despite the fact that RVS methods are more complex, the findings obtained as a result of the implementation of developed hierarchical FIS-based RVS method demonstrate significantly higher accuracy in terms of truly determining damage states. Finally, this study has demonstrated the promising applicability of a developed FIS-based RVS method by providing 67.5% accuracy. However, there is still room for further improvement.

Because the limited amount of post-earthquake screening data utilized restricts the application of computer algorithms such as machine learning and neural networks, in the event that more building screening data become available in subsequent studies, it is recommended that these algorithms be used and that results are compared with those obtained employing the current developed RVS approach. To conclude, because the number of buildings in each damage state is not evenly distributed, future research should consider utilizing additional and evenly distributed post-earthquake building screening data.

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**Abbreviations**
The following abbreviations are used in this manuscript:

- **RVS** Rapid Visual Screening
- **URM** Unreinforced Masonry
- **PVA** Preliminary Vulnerability Assessment
- **DVA** Detailed Vulnerability Assessment
- **FEMA** Federal Emergency Management Agency
- **GNDT** National Group for the Defense against Earthquakes
- **OASP** Earthquake Planning and Protection Organization
- **EMPI** Earthquake Master Plan for Istanbul
- **RBTE** Principles for Identifying Risky Buildings
- **NZSEE** New Zealand Society for Earthquake Engineering
- **NRC** National Research Council
RISK-UE An advanced approach to earthquake risk scenarios
Project with applications to different European towns
EMS-98 European Macroseismic Scale 1998
FIS Fuzzy Inference System
YC Year of Construction
LC Low Code
MC Moderate Code
HC High Code
SSH Site Seismic Hazard
$S_a$ Spectral Acceleration
FLS Fuzzy Logic System
MF Membership Function
PGA Peak Ground Acceleration
ASCE American Society of Civil Engineers
FS Final Score
CM Confusion Matrix

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