Disaster resilience quantification of communities: A risk-based approach

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ABSTRACT

Community and infrastructure resilience against natural and man-made hazards is paramount for the well-being of modern societies. To adapt to the fast-changing world, having communities that can effectively respond to the continuously changing (physical and social) environment is essential. Despite the existing literature on resilience definition and estimation, few frameworks and associated tools can effectively help decision-making. In addition, these tools are usually not well integrated into the community and infrastructure management processes so that decision-makers and authorities can effectively use them. This paper aims at developing a resilience-based risk assessment approach at the community level. It combines the risk analysis parameters with the intrinsic resilience of the community. The proposed approach offers essential insights into the quantitative resilience analysis of communities at different scales and for different natural hazards. It enables the combination of the risk parameters (hazard, exposure, and vulnerability) with the inherent resilience of all the systems that constitute a community. This paper also presents an easy-to-interpret tool for visualizing the resilience results obtained from the introduced approach. It translates the paper’s scientific contribution into an interactive and visualization instrument that can ultimately support policymaking to ensure their communities’ short and long-term resilience under known and unknown hazardous events.

1. Introduction

Previous natural and man-made disasters demonstrate that current communities are not highly resilient. Consequently, research on disaster resilience has been recently fostered. The term “resilience” is defined differently depending on the research field. The term resilience was defined by Ref. [1] as “the ability of a system to remain in a practical state and to degrade gracefully in the face of internal and external changes.” Other researchers have defined resilience as “the ability of social units to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities to minimize social disruption and mitigate the effects of future earthquakes” ([2–4]). For the sake of this study, the latter definition is adopted hereafter because it serves well the paper’s objective. Moreover, we extend the definition of resilience in this paper to consider the case where a system can recover to a higher state than the pre-disaster state.

Numerous community and system resilience assessment methods are available in the literature [5,6]. [7] proposed a framework to evaluate the disaster resilience of communities quantitatively. They introduced a list of resilience measures in a probabilistic context based on [2]. [8] introduced metrics to quantify the economic resilience of engineering systems. These metrics are fundamental for...
developing practical decision-making tools in multi-hazard environments. [9], developed a method that combines dynamic modeling with resilience analysis. [10] proposed a framework to analyze infrastructure resilience, establishing an expected annual resilience metric by defining a series of resilience-based improvement strategies for each stage. [11] have developed a probabilistic framework to evaluate the resilience of engineering systems. They overcome the static nature of resilience indicators by using the Dynamic Bayesian Networks.

Resilience indicators provide a way to overcome the complexity of community systems while computing their resilience. Several resilience quantification methods rely on the use of indicators. For example, [12] introduced the Hyogo Framework for Action (HFA), an international long-term top-down framework to improve the resilience of nations by implementing resilience measures at the government and policy levels. Building upon the Hyogo Framework, [13] introduced a quantitative approach to estimate resilience at the country level. [14] introduced the Baseline Resilience Indicator for Communities (BRIC), another quantitative top-down resilience framework that focuses on the inherent resilience of communities. An example of a qualitative resilience framework is the San Francisco Planning and Urban Research Association framework (SPUR) [15]. SPUR was developed to estimate the ability of a community to recover from seismic events. It considers the recovery capacity of buildings, infrastructures, and services to determine the resilience of the physical infrastructure. [16] developed the PEOPLES framework, a top-down theoretical framework that addresses all aspects of a community to estimate the community resilience. These aspects are grouped under seven community dimensions: Population; Environment; Organized government services; Physical infrastructure; Lifestyle; Economic; and Social capital. [13,17] have recently converted the PEOPLES framework into a quantitative framework for measuring community resilience. PEOPLES framework is one of the most promising resilience frameworks due to its capability to address all community resilience aspects in a (near) objective manner. Therefore, the PEOPLES framework is adopted in this paper as the community resilience blueprint for defining resilience by using its comprehensive indicators and structure. The PEOPLES framework will be introduced in detail in the next section.

Despite this robust literature on community resilience quantification, there is still a clear gap in the integration of risk analysis with the intrinsic resilience of communities. Moreover, by looking at the literature, there is currently an overwhelming number of tools and frameworks to support infrastructure management, and this number continues to increase. These are mostly left unexploited due to a lack of science-practice translation. Examples of frameworks that have been developed but never translated into working tools are: Department for International Development (DFID) Interagency Group [18], ResilUS [19], the Community Resilient System [20], the Communities Advancing Resilience Toolkit (CART) [21], the Conjoint Community Resiliency Assessment Measure (CCRAM) [22], and San Francisco Planning and Urban Research Association framework (SPUR) [15].

These tools need to be seamlessly integrated into the management processes so that infrastructure managers can effectively use them [5]. Therefore, there is a dire need for a decision support tool that the infrastructure managers can use to effectively exploit the different and constantly changing tools to determine the optimal risk-reducing intervention programs and, hence, prioritize their investments.

The primary goal of this paper is to overcome the shortcomings mentioned above by introducing a novel community resilience framework and an associated assessment tool that combines the risk analysis parameters with the intrinsic resilience of the community. The developed framework and its associated tool are primarily based on the PEOPLES framework by utilizing its comprehensive definition of community resilience. The contributions of this work are summarized as follows:

1) Main contribution: a resilience assessment methodology that is an evolution of the Resilience-Based Risk approach introduced in Ref. [13]. The proposed methodology offers essential insights into the quantitative resilience analysis of communities at different scales and for different natural hazards. It enables the combination of the risk parameters (hazard, exposure, and vulnerability) with the inherent resilience of all the systems that constitute a community. The significance of the proposed methodology lies in its capability and graphical representation that helps communities take proper actions to improve their resilience.

2) Secondary contribution: a visualizing tool offering an easy-to-interpret map for decision-makers. This tool is designed to convert the results into shapefiles or other geographical formats. It also allows one to interactively visualize attribute data and shapes of each community system (e.g., Municipalities).

The resilience quantification methodology and related software tool presented in this paper can be used as a decision-support tool by decision-makers to (i) learn about the state of their communities in the face of a particular event and (ii) prioritize planning and management strategies to improve the resilience of their communities to future hazardous events. The remainder of the paper is organized as follows. Section 2 reviews the PEOPLES framework and its seven dimensions, which are the basis of the developed methodology in this paper. Section 3 describes the proposed methodology for estimating community resilience. Section 4 presents an application of the proposed resilience estimation method to the municipalities of the Italian territory. Section 5 introduces the software tool developed to accommodate the proposed methodology. Finally, conclusions are drawn in section 6.

2. Peoples framework

PEOPLES is a hierarchical framework developed at the Multidisciplinary Center of Earthquake Engineering Research (MCEER). The objective of PEOPLES is to identify the resilience capabilities of communities at different scales (spatial and temporal) and to anticipate potential responses of a community to future hazard events [23,24]. The PEOPLES framework consists of seven dimensions of a community divided into a set of components. Each component is further subdivided into several indicators. The seven dimensions are summarized by the acronyms PEOPLES as follows (see Fig. 1):
1. **D1**: Population and Demographics: accounts for the socio-economic composition of the community and estimates social vulnerabilities that could impact the emergency response and recovery systems.

2. **D2**: Environment and Ecosystem: measures the ability of the ecosystem and environment to recover pre-hazard conditions.

3. **D3**: Organized Government Services: considers the community services that must be guaranteed before and after a hazard event. This includes preparedness and mitigation strategies (before the event) and response and recovery plans (after the event).

4. **D4**: Physical Infrastructure: accounts for the facilities and lifelines that must be restored after a hazard event.

5. **D5**: Lifestyle and Community Competence: concerns the community’s capabilities (e.g., the ability to face complex problems and find appropriate solutions employing political networks) and perceptions (e.g., the judgments and feelings a community has about itself toward a positive change).

6. **D6**: Economic Development: consists of the community’s current economic state (static state) and its development and future growth (dynamic state).

7. **D7**: Social-cultural Capital: tackles the community’s attitude to bounce back to the pre-event conditions.

Every dimension of the PEOPLES framework is divided into a set of components, and every component is further divided into a set of indicators. This expansion of the dimensions captures all aspects of a community. PEOPLES framework contains 115 resilience indicators [17]. Each indicator is associated with a measure that allows the analytical evaluation of the indicator’s performance. Each measure is normalized between 0 and 1 using a fixed quantity known as the target value (TV). The target value is the optimal value that the measure can take, and it is considered the baseline for the indicator’s assessment [25].

Furthermore, the measures are classified into “static measures (S)” and “dynamic measures (D).” A static measure is a measure that is not impacted by a hazardous event. In contrast, a dynamic measure is a measure that is event-sensitive (i.e., the value of the measure changes following a hazard event). The variables (i.e., dimensions, components, and indicators) included in the PEOPLES framework do not contribute equally to the resilience output. Therefore, they are distinguished according to their importance. Each variable in the same group is assigned an importance factor (I). To represent the functionality of each variable within the PEOPLES framework, a set of parameters obtained from past events or by performing hazard analysis is needed: the initial functionality before the event $q_0$, the post-disaster functionality $q_1$, the functionality after recovery $q_r$, and the restoration time $T_r$ required to complete the recovery process.

The PEOPLES framework has also been implemented as an online tool (http://www.resiltronics.org/PEOPLES/logic.php). After providing all necessary data, the tool evaluates the analyzed community’s Loss of Resilience (LOR). The full description of the tool can be found in Ref. [26].

3. Risk-based resilience approach at the community scale

3.1. Mathematical formulation

The resilience assessment methodology presented in this paper is an evolution of the Resilience-Based Risk (RBR) approach introduced in Ref. [13]. According to Ref. [13], the RBR is an index that combines three factors: intrinsic resilience, hazard, and exposure, as given by Eq. (1).

$$RBR = (1 - R_{in}) \times H \times E$$ (1)
The RBR includes internal and external factors. The only internal factor is the system’s intrinsic resilience ($R_{in}$), which reflects the internal characteristics of the system. The resilience of a system is defined as its capacity to withstand and recover from a disaster within a short time and with no outside assistance [27] (Fig. 2). The external factors include the Hazard ($H$) and the Exposure ($E$). The former is defined as the dangerous phenomenon that may cause loss of livelihoods and service, social, economic, and environmental disruption, while the latter refers to the existing physical and social components that are prone to potential losses.

In the figure, $Q_{0}$ represents the system’s functionality performance at the initial state. The occurrence of a disaster at time $t_0$ causes damage to the system, and this produces an instant drop in the system’s functionality ($\Delta Q$). Afterward, the system is restored to a new functionality level $Q_r$ over the restoration period ($T_r = t_1 - t_0$). $Q_r$ can be higher, lower, or equal to the initial functionality of the system. This supports the idea of “build back better.” The Loss Of Resilience (LOR) is considered equivalent to the quality degradation of the system over the recovery period. This definition of resilience suggests that resilience is associated with the concept of system vulnerability [29], where both hazard and vulnerability are involved. Hence, Eq. (1) can be rewritten as follows:

$$R = \int_{t_0}^{t_1} \frac{Q(R_{in}, H, V, t)}{T_r} \, dt \quad (2)$$

The system’s functionality $Q(R_{in}, H, V, t)$ is a function of the intrinsic resilience $R_{in}$, hazard $H$, vulnerability $V$, and time $t$. This function can be split into three components, as given by Eq. (3).

$$Q(R_{in}, H, V, t) = Q_0(R_{in}) - \Delta Q(H, V) + \Delta Q_r(t) \quad (3)$$

where $\Delta Q_r$ represents the recovered functionality at time $t$ following the event. By substituting Eq. (3) in Eq. (2), Eq. (2) can be written as follows:

$$R = Q_0(R_{in}) - \Delta Q(H, V) + \int_{t_0}^{t_1} \frac{\Delta Q_r(t)}{T_r} \, dt \quad (4)$$

It is apparent from this definition that resilience depends on factors that are not affected by the disastrous event (i.e., static) and event-sensitive measures (i.e., dynamic). The initial resilience $Q_0$ is independent of the hazard and the recovery time. On the contrary, the drop of functionality right after the occurrence of the hazardous event $\Delta Q$ depends on both hazard and system vulnerability. At the same time, it is not affected by the recovery process. The recovered functionality $\Delta Q_r$ is associated with both hazard, and available services and actions started after the event. Under these conditions, Eq. (1) can be modified as given by Eq. (5).

$$RBR(t) = \left[ (1 - Q_0(R_{in})) + \Delta Q(H \times V) - \int_{t_0}^{t_1} \frac{\Delta Q_r(t)}{T_r} \, dt \right] \times E \quad (5)$$

A novel framework is herein proposed to assess the RBR at different community scales based on the functionality of each element (i.e., indicator) within the community. The PEOPLEs hierarchical framework proposed in Ref. [13] is adopted to identify all aspects of a community that contribute towards its resilience. The functionality function of each element is characterized by a set of three parameters: (i) initial functionality ($Q_0$), (ii) functionality drop ($\Delta Q$), and (iii) recovered functionality after the hazard’s occurrence normalized with respect to the recovery time ($\Delta Q_r(t)/T_r$). Finally, the RBR function is obtained by combining the functionality function of each indicator by using a weighting method. A detailed description of the methods used to assess the three functionality parameters and the weighting factors is given in the following sections.

3.2. Initial functionality

PEOPLEs framework represents the keystone of the methodology since it allows classifying all the elements of a community and provides a quantitative measure of their resilience. PEOPLEs framework is organized into a hierarchical scheme consisting of dimensions ($D$), components ($C$), and indicators ($I$). The dimensions are the different layers of a community (i.e., physical infrastructure, social, economic, etc.). These dimensions are the collection of more specific components. Each component is divided into a set of
indicators collected from a wide range of literature [13]. Each indicator is associated with a measure that portrays the functionality of the indicator at the initial state (Fig. 3).

$I_{i,j,k}$ represents the indicator associated with the $k$th community’s element under the $j$th component of the $i$th dimension. That is, for $i, j, k$ all equal to one, $D_1$ is the first dimension of the PEOPLES framework “$D_1$: Population and demographic”, $C_{1,1}$ is the first component under $D_1$ “$C_{1,1}$: Distribution/density”, and $I_{1,1,1}$ is the first indicator under $C_{1,1}$ “$I_{1,1,1}$: Population Density”. The detailed list of dimensions, components, and indicators is found later in Section 4.”

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**Fig. 3.** Functionalities of the indicators at the initial state based on PEOPLES framework.

**Fig. 4.** Definition of the event-sensitive functionality parameters.
To make each indicator computable, Eq. (6) is provided.

\[ I_{ijk} = \left( \frac{IV}{TV} \right)_{ijk} \]  

(6)

where \( IV \) is the indicator value that quantifies the functionality of the \( k \)th element, \( TV \) is the target value, which refers to the optimal quantity for the indicator to be considered fully resilient. It provides a baseline measure for the analyzed element [14]. Therefore, \( I_{ijk} \) is a normalized ratio between 0 and 1. This ratio tells you how far you are from the desirable quantity that you want to reach. For example, if the actual quantity of a specific indicator is 50 and the desired quantity is 70, then the ratio would be 50/70.

3.3. Functionality drop and normalized recovery function

The impact of a given hazardous event on the community is defined through the drop of functionality, recovered functionality over time, and restoration time. The drop of functionality right after the hazard occurrence is assessed according to the common risk analysis practices. In standard risk analysis, fragility functions are employed for assessing the probability of exceeding a certain level of damage \( DS \) conditioned on the hazard intensity \( IM \). The fragility value is then converted into a vulnerability measure using a damage-
to-loss model, which describes the relation between damage level and the related fraction of loss $\Delta Q$ [30]. The restoration time can be computed using restoration fragility curves available in the literature [31]. Finally, recovery functions may be chosen depending on the analyzed system and expected society response [32]. Fig. 4 illustrates the general workflow used for evaluating the event-sensitive functionality parameters.

The event-sensitive functionality parameters are defined in a probabilistic manner. The fragility functions are expressed by the conditional probability $f(DS/IM)$, while the expected level of loss conditioned on the damage level is given by $f(\Delta Q/DS)$. Then, the vulnerability is defined as the probability of having a specific loss given a hazard intensity ($f(\Delta Q(IM))$). Furthermore, the uncertainty on the assessment of the recovery time is expressed through the conditional probability $f(T_r/IM)$. This approach can be generalized to any community system (e.g., physical, economic, social, etc.), providing a set of expected functionality parameters within a given confidence interval.

3.4. Weighting-based method

The functionality functions associated with each analyzed performance indicator are obtained by combining the initial functionality with the potential drops and the recovery function. It is worth mentioning that some performance indicators are not event-sensitive; therefore, the functionality function of such indicators is a uniform function with a value equal to the initial functionality. All functionality functions are then weighted based on their contribution to the resilience assessment as given by Eq. (7).

$$R_0 = \frac{\sum_{i=1}^{n_d} w_i \left[ \sum_{j=1}^{n_c} \left( \frac{\sum_{k=1}^{n_i} w_{ij,k} \cdot I_{ij,k}}{\sum_{k=1}^{n_i} w_{ij,k}} \right) \right]}{\sum_{i=1}^{n_d} w_i}$$

where $n_d, n_c$, and $n_i$ are the number of dimensions, components, and indicators of the PEOPLES framework, respectively. The coefficients $w_i$ refer to the importance weight of the $i$th dimension, while $w_{ij}$ is the weight of the $j$th component under the $i$th dimension. Similarly, $w_{ij,k}$ and $I_{ij,k}$ represent, respectively, the importance weight and the PEOPLES indicator associated with the $k$th component under $j$th component, which belongs to the $i$th dimension. Both static and dynamic indicators are considered in the weighting methodology. The weights of the indicators in the same group are aggregated and transferred to the upper layer, and the same process is repeated for the components and the dimensions.

The weight of every indicator is determined as follows. First, an Importance Factor (IF) in the range 1–3 is assigned to each indicator. The IFs’ values are determined using a survey filled by disaster resilience experts. The indicator’s weight is then evaluated as given by Eq. (8). The weights for dimensions and components can be similarly assessed.

$$w_{ij,k} = \frac{IF_{ij,k}}{\max(IF)}$$

where $\max(IF)$ refers to the maximum importance factor recorded in a given group of variables (i.e., indicators, components, or dimensions).

3.5. Summary of the proposed framework

A deeper insight into the proposed framework is illustrated in Fig. 5, in which the entire computational workflow is summarized. To summarize, the community’s elements are classified based on the hierarchical scheme adopted for PEOPLES framework, which allows computing the initial functionality for each assumed indicator. The hazard intensity is correlated with the vulnerability of the community elements through the fragility functions and damage-to-loss models. The hazard intensity allows us to estimate the restoration time. The estimated functionality parameters are combined using a weighting-based method to assess the RBR function and the associated confidence interval. The required input data consist of (i) the information of the community’s element, (ii) the hazard intensity measure, (iii) the fragility functions and damage-to-loss models for the community’s elements, and (iv) recovery functions for the elements. The information of the community’s elements allows to identify the exposure and quantify the intrinsic resilience before the hazard. The hazard is characterized by its intensity measure $IM$. The combination of the hazard intensity with the fragility functions and damage-to-loss models leads to quantifying the resilience variation due to the hazardous event. Furthermore, restoration curves and functions are employed to model the recovery process and assess the recovered functionality after the event.

4. Real application of the proposed framework

The proposed framework is applied to the entire Italian territory to assess the RBR function for every Municipality. Due to practical constraints, the application of the proposed framework examines some of the PEOPLES dimensions for which the majority of the indicators are available. These dimensions are the Population and demographics, Environment and ecosystem, and Physical infrastructure dimensions. The collected data consists of the Indicator Values (IVs) and Target Values (TVs) of the indicators belonging to the dimensions above. The Importance Factors (IFs) of the PEOPLES variables have been defined based on expert judgments. For simplicity, the recovery capacity of the systems under consideration has not been accounted for. This assumption implies focusing on the immediate post-earthquake resilience while neglecting the functional recovery. This, in turn, leads to higher RBR index values since the term $\Delta Q(t)$ of Eq. (4) is set to zero. Therefore, the application in this paper focuses on the definition of the time-independent component of the RBR function. The application considers three hazards: earthquake, landslide, and flood. The information sources
and data processing approaches are described in detail in the following sections.

4.1. Hazard and exposure

The proposed framework enables accounting for the effect of hazardous events on the assessment of resilience. The definition of the hazardous scenario and the related exposed elements are vital aspects of the procedure. Three typical Italian hazards are considered in this study: earthquake, landslide, and flood. The related exposure and hazard data have been gathered from the Italian Statistical Institute (ISTAT), which provides the hazard maps and parameters of the Italian municipalities [33]. A Geographical Information System tool allows visualizing and downloading the earthquake, landslide, and flood hazard maps [34]. These data come from the different Research Institutions that operate in the field of seismic (National Institute of Geophysics and Volcanology) [35] and hydrogeological [36] hazards.

4.1.1. Earthquake

The entire national territory is deemed exposed to seismic hazards [37]. The seismic hazard is expressed in terms of the probability of earthquake occurrence at a given site, within a reference period, and with a particular ground motion intensity [38]. The Peak Ground Acceleration (PGA), characterized by a 10% probability of exceedance in 50 years, is considered the reference seismic intensity parameter in this study. The seismic hazard map containing the maximum PGA at each Italian site is provided by the National Institute of Geophysics and Volcanology [35] and is illustrated in Fig. 6-a.

4.1.2. Landslide

The data relating to the landslide hazard are derived from the Italian Landslide Inventory (IFFI) realized by ISPRA and the Regions and Autonomous Provinces [39,40]. The IFFI is a crucial tool in landslide hazard assessment of River Basin Plans (PAI), which allows

Fig. 6. Seismic hazard map for Italian territory.
identifying mitigation measures and civil protection emergency plans. The landslides of the IFFI are classified as active, quiescent, and stable. Active landslides are those in action or occurred in the last 30 years, while quiescent landslides refer to those active in a period preceding the last 30 years. Instead, in stable landslides, the equilibrium is reached through consolidation actions. In 2017, the Institute for Environmental Protection and Research (ISPR) established the National Mosaic of the landslide hazard zones of the River Basin Plans [41]. Five different hazard classes have been proposed, as listed in Table 1.

As an illustrative example, Fig. 7 depicts the Italian landslide map related to the mean exceedance probability in 50 years.

Moreover, ISPRA provides the exposure data for each hazard class in terms of population and buildings located within the hazardous zones. The hazard classification of the entire national territory shows some nonuniformities due to the different methodologies employed by the Basin Authorities in defining the landslide hazard. The return periods range between intervals based on the expected landslide magnitude (Table 1). Furthermore, the flow-velocity of the unstable mass of terrain is considered as IM parameter. This assumption is justified by the observation that about one-third of Italian landslides are characterized by a high velocity (i.e., the flow

| Class | Hazard | Description | Return period | Exceedance probability in 50 years |
|-------|--------|-------------|---------------|-----------------------------------|
| H14   | Very high | Active landslides and possible evolution of existing landslides | 30 years | 81% |
| H13   | High | Possible evolution of existing landslides | 100 years | 39% |
| H12   | Medium | Possible evolution of existing landslides | 300 years | 15% |
| H11   | Moderate | Possible evolution of existing landslides | 500 years | 10% |
| AA    | Attention zones | Active landslides and assessment of hazard class in progress | – | – |

Fig. 7. Landslide hazard map for the Italian territory.
velocity is up to a few meters per second) and with high disruptive power [42]. According to the classification proposed by Ref. [43], a mean velocity of 2.5 m/s of landslide is considered as rapid.

It is worth mentioning that a more detailed local analysis on landslides triggering factors and geological features of the site is crucial to characterize the hazard and define the related intensity parameters (e.g., flow velocity, permanent soil displacement, geometric severity).

### 4.1.3. Flood

In 2007, the European Community released the Floods Directive (FD) to establish a framework for assessing and managing flood risk in Europe. The FD was introduced in Italy with the D. Lgs 49/2010 and represented the reference for flood risk mitigation and management within the national territory. In 2017, ISPRA released the new National Mosaic of the flood hazard zones the River Basin District Authorities provided. The Italian territory is classified into three hazardous zones based on the return period (Table 2).

The flood hazard map associated with the national territory is illustrated in Fig. 8.

Table 2 reports the exposure data for each hazard class in terms of population and buildings located within the hazardous zones.

#### Table 2

| Class | Hazard                               | Return period | Exceedance probability in 50 years |
|-------|--------------------------------------|---------------|-----------------------------------|
| H_F3  | High probability scenario            | 50 years      | 63%                               |
| H_F2  | Medium probability scenario          | 200 years     | 22%                               |
| H_F1  | Low probability scenario             | 500 years     | 10%                               |

Fig. 8. Flood hazard map for the Italian territory.
The occurrence probabilities in 50 years are also reported. Generally, the intensity measure of the flood is defined by flow velocity, water depth, and debris volume. These parameters can be obtained through accurate local analyses by employing different methodologies. Since no detailed information is provided for each hazardous zone within the National territory, the water depth is assumed as IM with a mean value of 1 m for all the hazard classes.

4.2. Initial functionality

The initial functionality of the community’s element is expressed by the set of indicators. They are calculated based on the collected data properties of the three analyzed dimensions.

| Dimension (Di) | Component (Ci) | Indicator Values (Ivi) (Ivi) | Data source | Scale | Year | Nature |
|---------------|----------------|-----------------------------|-------------|-------|------|--------|
| Population and demographic | Distribution/density | Population Density | ISTAT | Municipality | 2011 | Dynamic |
| | Composition | % of the population living in an urban area | ISTAT | Municipality | 2011 | Static |
| | | % of active population [18-65] | ISTAT | Municipality | 2011 | Static |
| | | % of not foreigner arrived within last 5 years | ISTAT | Municipality | 2011 | Static |
| | | % of population changed over last 5 years | ISTAT | Municipality | 2011 | Static |
| | | % of the minority population | ISTAT | Municipality | 2019 | Static |
| | | % white and nonwhite people | ISTAT | Municipality | 2019 | Static |
| | | % of two-parents family | ISTAT | Municipality | 2019 | Static |
| | | % of female and male | ISTAT | Municipality | 2019 | Static |
| Socio-economic status | | % of the population with college degree | ISTAT | Municipality | 2019 | Static |
| | | % of the population with less than high school education | ISTAT | Municipality | 2019 | Static |
| | | % of owner-occupied housing units | ISTAT | Municipality | 2011 | Dynamic |
| | | Gini coefficient | ISTAT | Regional | 2019 | Static |
| | | male income - female income | ISTAT | Country | 2019 | Static |
| | | Per-capita household income | ISTAT | Municipality | 2019 | Dynamic |
| | | % of the population whose income is below minimum wage | ISTAT | Municipality | 2019 | Dynamic |
| | | % of employment rate | ISTAT | Municipality | 2011 | Dynamic |
| Environment and ecosystem | Water | number of river miles whose water is useable | ISPRA | Province | 2018 | Static |
| | Air | air quality index | ISPRA | Province | 2018 | Static |
| | Soil | % of land in wetlands | ISPRA | Municipality | 2018 | Static |
| | | average % perviousness | ISPRA | Municipality | 2018 | Static |
| | | % of land area that does not contain erodible soils | ISPRA | Municipality | 2018 | Static |
| | Biodiversity | % of species vulnerable to extinction | – | – | – | Static |
| | Biomass | harvest index | – | – | – | Static |
| | | normalized difference vegetation index | – | – | – | Dynamic |
| | Sustainability | % of land area that is undeveloped forest | ISPRA | Municipality | 2018 | Static |
| | | % of land area with no wetland decline | ISPRA | Municipality | 2018 | Static |
| | | % of land area with no land-use change | – | – | – | Static |
| | | % of land area under protected status | – | – | – | Static |
| | | % of land area that is arable cultivated land | – | – | – | Static |
| Physical infrastructure | Facilities | % of housing units that are not manufactured homes | ISTAT | Municipality | 2011 | Dynamic |
| | | % of vacant units for rent | ISTAT | Municipality | 2019 | Dynamic |
| | | % of housing units built prior to 1970 | ISTAT | Municipality | 2011 | Dynamic |
| | | % of the total area of community services | – | – | – | Dynamic |
| | | % of commercial establishments outside of high hazard zones/total commercial establishment | ISTAT/ISPRA | Municipality | 2011/2018 | Static |
| | | % of commercial infrastructure per area | ISTAT | Municipality | 2011 | Dynamic |
| | | number of hotels per total area | ISTAT | Municipality | 2011 | Dynamic |
| | | school area (primary and secondary) per population | DataOpen: Ministry of University and Research | Municipality | 2011 | Dynamic |
| Lifelines | | average no of telecommunication systems per household | – | – | – | Dynamic |
| | | no of beds per 1000 population | – | – | – | Dynamic |
| | | no of physicians per population | – | – | – | Static |
| | | no of available hospital beds per 1000 population | DataOpen: Ministry of Labour and Social Policies | Municipality | 2011 | Dynamic |
| | | major road egress points per building | – | – | – | Static |
| | | rail miles per total area | – | – | – | Dynamic |
| | | % of the population with access to the internet | – | – | – | Dynamic |
| | | the ratio of megawatt power production to demand | – | – | – | Dynamic |
| | | the ratio of water available to water demand | ISTAT | Municipality | 2011 | Dynamic |
| | | the ratio of gas production to gas demand | – | – | – | Dynamic |
| | | principal arterial miles per total area | – | – | – | Dynamic |
| | | no of rail miles per area | – | – | – | Dynamic |
| | | no of WWT units per population | – | – | – | Dynamic |

The occurrence probabilities in 50 years are also reported. Generally, the intensity measure of the flood is defined by flow velocity, water depth, and debris volume. These parameters can be obtained through accurate local analyses by employing different methodologies. Since no detailed information is provided for each hazardous zone within the National territory, the water depth is assumed as IM with a mean value of 1 m for all the hazard classes.

4.2. Initial functionality

The initial functionality of the community’s element is expressed by the set of indicators. They are calculated based on the collected...
The IV associated with the three analyzed dimensions at municipality scale have been collected by exploiting the following sources:

- The Italian Statistic Institute (ISTAT) provides census data for population composition, environment, energy, social assistance, incomes, culture, business, education, healthcare, tourism, transportation, and buildings. The data are available through the web tool “Atlante Statistico dei Comuni” at the link http://asc.istat.it/ASC/ and on the permanent census data warehouse at the link http://dati-censimentipermanenti.istat.it/?lang=it.
- Open data released by different Public Institutions at the link http://www.datopen.it/. The open data related to schools and healthcare facilities have been collected for each Municipality.

| Damage State | Damage ratio |
|--------------|--------------|
|              | Median ($\mu_{Q/DS}$) | Dispersion ($\sigma_{Q/DS}$) |
| DS1          | 1             | 0.17                     |
| DS2          | 10            | 1.67                     |
| DS3          | 35            | 6.67                     |
| DS4          | 75            | 13.33                    |
| DS5          | 100           | 0                        |

Fig. 9. Seismic building vulnerability map of Italy.
Table 5
Ductility level based on the building year of construction.

| Ductility Level | Year of construction |
|-----------------|----------------------|
| Low             | pre-1981             |
| Medium          | 1982-2008            |
| High            | post-2009            |

Table 6
Damage ratios associated with the selected landslide DSs.

| Damage State | Damage ratio | Median ($\mu_{Q/DS}$) | Dispersion ($\sigma_{Q/DS}$) |
|--------------|--------------|------------------------|-------------------------------|
| DS2          | 10           | 3.33                   |
| DS3          | 35           | 5.00                   |
| DS4          | 75           | 8.33                   |

- Institute for Environmental Protection and Research (ISPRA) which provides metadata on environmental systems such as soil use (https://www.isprambiente.gov.it/it/banche-dati/banche-dati-folder/suolo-e-territorio/uso-del-suolo) and air quality (https://annuario.isprambiente.it/sys_ind/macro/1).
- When the data are not available at the municipality scale, the information collected at the Province, Region, or Country level has been considered a reference. Table 3 lists all the collected data by specifying the reference scale, the information source, and the related year. Each considered indicator is classified as static or dynamic, depending on whether they are independent or event-sensitive.

Most of the buildings and demographic information at the municipality scale refer to the most recent detailed population and buildings conducted by Census in 2011. The total number of Municipalities within the national territory equals 8092 with a population of 59, 433, 744. Census also examines 12, 187, 698 residential and 2,264,982 non-residential building units.

4.3. Target values (TVs)

An expert judgment method is adopted to assess the TV for each considered indicator in the present work. According to the selected indicators listed in Table 3, a survey has been distributed among a group of experts who provided an educated guess on the TVs based on their experience. Each TV has been treated as a normally distributed Random Variable (RV) truncated at zero with mean and standard deviation calculated based on the expert judgments scores. This statistical approach leads to considering the inherent uncertainties. Hence, the resilience index may be expressed in terms of mean value ($\bar{TV}$) and related standard deviation ($\sigma_{TV}$).

4.4. Functionality drop

The loss of functionality of exposed elements is accounted for through fragility models. Many researchers provided empirical fragility models for different hazards and systems such as buildings [44–47], lifelines [48,49] [50,51], socio-economic systems [52], business services [53]. Among the different exposed elements to natural disasters, the building portfolio represents the most crucial asset within a community [54,55]. The availability of detailed census data on the Italian building stock allows us to account for their loss of functionality using empirical fragility curves and predefined damage-to-loss models. Therefore, in this application, the functionality drop caused by seismic, landslide, and flood hazards has been considered for the building portfolio only, while the exposure values are obtained from the census data.

4.4.1. Vulnerability model for seismic hazard

In this work, the fragility functions proposed by Ref. [56] have been adopted for Reinforced Concrete (RC) and Unreinforced Masonry (URM) buildings, respectively. The buildings are classified based on their total height and year of construction, which is directly connected to the design level. The PGA is assumed as the IM parameter, while the damage classification, which is consistent with the European Macroseismic Scale (EMS [57], consists of five damage levels (DS1: slight or negligible damage, DS2: moderate damage, DS3: severe damage, DS4: very heavy damage and DS5: collapse). The related damage-to-loss model proposed by Ref. [58] has been herein assumed to evaluate the median damage ratios, while the related dispersion values are calculated based on the ATC-13 ranges [59] (Table 4). The damage ratio is assumed to represent the building functionality drop and identifies the repair/recovery cost ratio to building replacement cost.

The vulnerability map of the national building stock is illustrated in Fig. 9 with reference to the median values of probability of exceeding the DS4.

4.4.2. Vulnerability model for landslide hazard

The flow-type landslide fragility function proposed by Ref. [47] has been considered in this application. The fragility functions refer to RC frames with infilled masonry panels, with different level of ductility (low, medium, high). Since no detailed information on the ductility level of the building portfolio is provided, a simplified procedure is adopted to classify the buildings based on the year of
construction. Based on the design classification proposed by Ref. [56] and on the main changes in the seismic Italian design regulations, the building portfolio is herein classified as listed in Table 5.

The landslide flow velocity is considered as the IM parameter. Three damage states are assumed for RC frame are moderate (DS2), heavy (DS3), and very heavy (DS4) damage. The damage-to-loss model proposed by Ref. [60] has been assumed in this application for the three selected DSs (Table 6).

The out-of-plane collapse fragility function proposed by Ref. [61] is adopted for masonry buildings. This assumption tends to overestimate the drop of functionality for the entire building, assuming only the collapse damage level (total drop of functionality). For both fragility models, the landslide flow velocity is considered as IM parameter. The vulnerability map of the national building stock is illustrated in Fig. 10 with reference to the median values of probability of exceeding the DS4.

4.4.3. Vulnerability model for flood hazard

Current methodology in the field of flood risk assessment employs global damage functions to compute the amount of potential losses instead of fragility functions [62]. proposed a set of damage functions for different classes (e.g., buildings, transportation, etc.) at the continent level based on the flood depth. The European damage function model related to the building class is adopted herein for RC and masonry buildings. The assessed level of damage represents the functionality drop due to the building structure and contents. As an illustrative example, a flood vulnerability map related to the flood depth H3 is depicted in Fig. 11 with reference to the building class.

4.5. Weights

Indicators do not contribute equally to the overall resilience output; therefore, they must be weighted in a specific way to successfully aggregate them into one scalar number [63]. In the present study, the importance of each indicator and component is
expressed with a score of: 1 (low importance), 2 (medium importance), and 3 (high importance). A survey is conducted to collect the expert-judgments scores. Then, the weight of each indicator is computed using Eq. (7). Statistical analysis is performed to account for the variability in the IF scores resulting from the survey. Each weight is assumed as a normally distributed RV truncated at zero with a given mean \( \mu_w \) and standard deviation \( \sigma_w \).

4.6. RBR index

For each community’s element considered in the application, the related kth indicator under the jth component and ith dimension is calculated as given by Eq. (9).

\[
I_{ijk} = \begin{cases} 
\left( \frac{IV}{TV} \right)_{ijk} & \text{for : static indicators} \\
\left( \frac{IV}{TV} \right)_{ijk} - \Delta Q_k & \text{for : dynamic indicators}
\end{cases}
\]  

(9)

where \( \Delta Q_k \) refers to the loss of functionality of the element exposed to given hazards.

As previously discussed, the functionality drop is computed for each DS and is characterized by the median and dispersion values. According to Ref. [64], the fragility and loss functions can be combined to compute the mean and variance of the loss for a given level of IM as given by Eq. (10).
\[ \mu_{Q/IM} = \sum_{d=1}^{N_{DS}} \mu_{Q_{(DS)}} \cdot f(DS/IM) \cdot f(IM) \]

\[ \sigma_{Q/IM} = \sqrt{\sum_{d=1}^{N_{DS}} \left[ \mu_{Q_{(DS)}}^2 + \sigma_{Q_{(DS)}}^2 \right] \cdot f(DS/IM) \cdot f(IM) - \mu_{Q/IM}^2} \]

where \( N_{DS} \) represents the total number of DS considered in the vulnerability model, while \( f(IM) \) refers to the probability of exceeding a specific IM value in a reference period. A reference period of 50 years has been assumed for all the hazards in this example. Eq. (9) combines the fragility function with the hazard intensity through the total probability theorem. Based on Eq. (9), the loss of functionality \( \Delta Q_k \) is then expressed as an RV with given median \( \mu_{Q/IM} \) and standard deviation \( \sigma_{Q/IM} \). Finally, the RBR function is calculated through the weighting procedure given in Eq. (7) using the set of mean weights for each indicator, component, and dimension. Due to the random nature of the functionality losses and weights, the RBR index is an RV. Therefore, a Monte Carlo Simulation can be alternatively adopted to consider the randomness of the variables used to compute the RBR function. This approach leads to an expected value of resilience and the related confidence interval at the municipality scale. In the proposed application, the median values of losses and the mean weights have been assumed, while a reference period of 50 years is considered to characterize the hazards. Fig. 12 summarizes the proposed approach used in the application to assess the RBR index at the municipality scale.
5. Software tool implementation

The proposed framework for the resilience assessment has been transformed into a software tool specifically for the communities within the Italian territory. Matlab© programming language is used for software implementation [65]. Although the tool is developed in Matlab, it is an independent tool that can be downloaded and used like any other software. It is freely accessible and downloadable: Tool-for-Disaster-Resilience-Quantification-of-Communities (github.com).

The analysis flow is based on the PEOPLES framework. The data have been collected for each Municipality and organized into a database that reflects the PEOPLES framework structure related to dimensions 1, 2, and 4 (Table 3). The database also consists of exposure and hazard parameters. The latter are expressed in terms of the expected hazard intensity with a certain exceedance probability in 50 years. The developed software aims at calculating the initial functionality based on the collected data and the mean target values extracted from the survey filled by experts in the resilience field. According to the procedure illustrated in Fig. 3, the software estimates the drop of functionality caused by earthquakes, landslides, and floods. It is worth mentioning that the drop of functionality refers only to the building portfolio whose collected data are detailed for the whole national territory. Finally, the RBR index associated with each Municipality is evaluated according to Eq. (5) and converted into a shapefile automatically visualized in mapshaper [66]. This tool allows to interact with the obtained results and edit them through a web interface. The software includes a user-friendly graphical interface (Fig. 13) that allows managing the input parameters such as the weight related to the indicators, components, and dimensions.

Target values and essential factors are automatically calculated based on the survey results. The software allows visualizing and editing the indicators’ attributes by clicking on the indicator’s description (Fig. 14). The component and dimension weights are set to 1.
by default. Moreover, the user can edit the weight values by clicking on the related component or dimension’s description.

Once the indicator target values and the dimension, component, and indicator weights are set, the RBR index of each Municipality within the Italian territory is calculated. The software will generate a shapefile containing all the information about the RBR index,
while the map is automatically shown on the mapshaper web tool. Fig. 15 illustrates the RBR index map by considering dimensions 1, 2, and 4 only.

Fig. 15 highlights how the lower values of the RBR index are related to the municipalities along the Apennines arch. The lowest values are recorded on Calabria, Sardinia, Sicily, and some Municipalities located in the North-west Alpes and Veneto Region. The RBR index map has also been generated considering only dimensions 1, 2, and 4 (Fig. 16).

The population and demography characteristics (Fig. 16-a) reveal that southern Italy is consistently less resilient than the Northern regions. No considerable differences have been identified for the environmental and ecosystem dimension, which shows almost uniform characteristics for the whole national territory (Fig. 16-b). The RBR index associated with the physical infrastructure (Fig. 16-c) assumes lower values in the Apennines arch, Calabria, Sardinia, North Terranea zone, and part of the Alpes belt. According to Figs. 6, Figure 7, and Fig. 8, the areas mentioned above are located in seismic and landslide hazard-prone areas, whereas they have higher vulnerability than the remaining Italian territory.

The higher values of the RBR index are recorded in the geographical region of the Po valley. Despite the zone being located in a flood-prone area, the hazard and exposure to earthquakes and landslides is limited.

The proposed methodology can evaluate the additional loss of functionality on the building portfolio due to the earthquake, landslide, and flood hazards. In order to emphasize this aspect, only the indicators associated with the building portfolio (I-56 in PEOPLES framework) have been considered in the calculation of the RBR index. To do this, all importance factors associated with other aspects have been set to zero. Fig. 17 depicts the RBR index map associated with earthquake, landslide, and flood hazards are taken individually.

The RBR indices are calculated by considering only the building loss of functionality due to the three analyzed hazards. In all three cases, the RBR index maps perfectly match the reference Italian hazard maps for earthquake, landslide, and flood.

6. Concluding remarks

This paper introduces a novel resilience assessment framework at the community level. It combines the risk analysis parameters with the intrinsic resilience of the analyzed community. The introduced framework offers important insights into the quantitative resilience analysis of communities at different scales and for different natural hazards. It enables the combination of the risk parameters (hazard, exposure, and vulnerability) with the inherent resilience of all the systems that constitute a community.

The framework has been applied to all municipalities within the Italian territory while considering three natural hazards (i.e., earthquake, landslide, flood) in the loss of functionality calculation. A visualization tool with an easy-to-interpret map has been developed to communicate the results. This tool allows one to visualize attribute data and shapes of each community interactively. It makes it easy for decision-makers to see and interpret the results without dealing with the computational complexity. Among other results, every community obtains a resilience index. This index is to indicate whether the community needs to improve in terms of resilience by comparing it to a given acceptable level. The implemented software can automatically calculate the input parameters based on the survey results while allowing the user to edit any input parameters. Some examples of input setting and visualization of the results have been given. Using the proposed tool, decision-makers can identify immediately if a community is experiencing a high serviceability deficiency. The decision-maker can then decide to investigate specific components and indicators that are causing the highest impact on resilience.

The significance of the proposed methodology lies in its capability and graphical representation that helps communities take proper actions to improve their resilience. While all previous works generally provide a single index to measure community resilience, the proposed method indicates in detail whether the resilience deficiency is caused by the system’s lack of robustness or by the slow restoration process. The proposed method identifies where resources should be invested to improve resilience efficiently.
Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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