Resilience assessment at the regional level using census data

(Article begins on next page)

Resilience Assessment at The Regional Level Using Census Data

Alessandro Cardoni[a], Ali ZamaniNoori[b], Rita Greco[d] Gian Paolo Cimellaro[c]

[a]Ph.D. Student, Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Turin, Italy. E-mail: alessandro.cardoni@polito.it

[b]Postdoctoral research associate, Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Turin, Italy. E-mail: ali.zamani@polito.it

[c]Associate Professor, Department of Civil Engineering, Politecnico di Bari, Via Amendola 126/b - 70126 Bari, Italy. E-mail: rita.greco@poliba.it

[d] Professor, Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Turin, Italy. E-mail: gianpaolo.cimellaro@polito.it

Abstract

Over the last decade, the topic of regional resilience has drawn the attention of public authorities due to the increasing number of natural disasters. The absence of a practical and concrete methodology makes it extremely difficult to evaluate resilience at the regional scale, which involves several concepts such as economics, social sciences, environment, etc. This paper proposes an indicator-based approach to assess the resilience assessment of Italian regions. A set of twelve indicators has been selected among publicly available census data. A time window of ten years was considered in the analysis. Three different resilience indexes were calculated for each region. The first is an overall measure of resilience, while the other two represent resilience during the emergency and the restoration phase following a disaster. Results highlight fundamental aspects that have a higher impact on regional resilience and can be used by decision-makers to effectively allocate resources. The procedure has also been extended to evaluate the regional epidemic risk which can be used as a preliminary tool to develop risk mitigation strategies against biological hazards.

Keywords: resilience assessment; indicator-based approach; regional resilience; census data; emergency management.

1. Introduction

In the past two decades, several studies have been conducted to address the resilience of communities, interconnected systems, and networks. By looking at available resilience definitions in the literature, it can be considered as a process leading to an improvement of current conditions, whether it is a safer city, a more robust infrastructure, a cost-effective policy, etc. Resilience includes a variety of aspects such as community preparedness, code adoption and enforcement, and hazard mitigation. To account for all these characteristics, proper resilience frameworks need to be designed. Usually, these are grouped according to their spatial scale (e.g., city, region, country).

By looking at the available frameworks, there is no single or widely accepted method to quantify community resilience [1]. Overall, resilience measurement approaches can be classified into four different groups. The first group consists of schemes based on scorecards to evaluate the performance of a given system. Scorecards are in the form of checklists that identify a series of qualitative questions about the presence or absence of certain features and actions. Each question is associated with a score and the total resilience of the system is measured by adding all scores. The second group is based on indicators or indices that provide a quantitative measure of the system's resilience[2]. Indices are representative of system characteristics and can be statistically evaluated. The overall system resilience is computed by an aggregation of the selected indexes. The third group is based on the combination of scorecards and indices providing tools for resilience assessment (such as guidance, surveys, procedures, or data)[3]. Lastly, the fourth group gathers approaches that use mathematical models to simulate interactions and relationships within the analyzed system. Those models can be used to measure various resilience dimensions of the system (such as physical, social, economic, etc.) through computational simulations [4; 5].

The United Nations International Strategy for Disaster Reduction (UNISDR) is an example of a city-level framework that evaluates community resilience against natural disasters [6]. The methodology is based on scorecards that identify priorities for investments and track the status of the city over the recovery time. However, the framework is not practical to apply in real case scenarios. Additional information is required to assess the performance of critical networks and their interdependencies. Furthermore, there is not a specific metric tool to assess recovery time considering all community dimensions such as social and economic aspects.

The National Institute of Standards and Technology (NIST) [7] proposed a city-scale resilience framework based on a comprehensive list of community indicators. It summarizes the available guidance, tools, and metrics considering different hazard intensities. The framework presents three different metrics to compute the overall community resilience (i.e., recovery time, economic metrics, and social metrics). However, these parameters are defined in terms of guidelines without a specific description of how to use and apply them in practice.

Another example is represented by the Oregon resilience plan, which was built upon the SPUR (Social, Psychological, Usage, Rational) framework that was specifically developed for the city of San Francisco [8]. Compared to the SPUR framework, it provides a methodology to better evaluate resilience in the economic dimension, but it does not quantify social aspects.

A more comprehensive methodology is represented by PEOPLES framework [9], a multidimensional resilience framework that can be applied from the city level to the country level. It is also capable of modeling interdependencies among different community layers [10]. However, it provides a qualitative assessment rather than a quantitative measure.

Even though remarkable efforts have already been made to boost research on community resilience [11-13], there is still not a universally accepted methodology [14]. Chang and Shinozuka [15] proposed a series of resilience measures in a probabilistic formulation based on the work done by Bruneau et al. [16]. Furthermore, Ayyub [17] defined practical resilience metrics related to the concepts of reliability and risk. Liu et al. [18] introduced a method that combines dynamic modeling with resilience analysis. They investigated the response of interdependent critical infrastructures by performing a numerical analysis of their conditions in terms of design, operation, and control for a given failure scenario. Overall, there is a lack of clarity and consistency of key concepts across different resilience frameworks, especially concerning social aspects [19-21].

The use of indicators is perceived as an important tool to measure the resilience of a system. Yet developing a standardized set of resilience indicators is challenging for such a dynamic and context-dependent concept. This is particularly true at the regional and country level. In addition, for such large-scale analyses, data paucity is a common issue that needs to be overcome.

This paper presents a novel indicator-based approach to measure resilience at the regional scale using only publicly available statistical data. The selection of indicators is based on PEOPLES framework's dimensions and components. To translate these indicators from a qualitative measure into a quantitative measure, their interdependency and importance were evaluated through a survey and combined to obtain weighting factors. The methodology is applied to the twenty Italian regions to evaluate the seismic resilience under three scenarios: normal conditions, emergency phase, and restoration phase. The procedure is then extended to evaluate the regional risk towards the spread of an epidemic. Results are discussed and compared to the recent events regarding the novel coronavirus.

2. Data collection and selected indicators

When dealing with resilience assessment at any scale, the first issue to face concerns data collection. In many situations, however, not only data quality is a problem but also scarcity. Indeed, data is often incomplete or not available in the first place. Especially at large scale, it is likely that the information needed to carry out resilience analyses is hold by private authorities and stakeholders who are not always willing to share it. The idea of this research is to perform a resilience assessment at the regional scale using only publicly available data records. Depending on the case study, different public sources might be accessible. The crucial aspect is to select only information that has a positive or negative contribution to regional resilience. Any available resilience framework can be followed. Nonetheless, it is worth noting that most frameworks either do not provide a quantitative way to measure resilience or they propose some metrics which not necessarily match the resources in available databases. Thus, it is unlikely that one framework can be followed thoroughly, and some adaptations should be made [22].

This paper aims at providing a resilience measure of the 20 regions in which Italy is divided. To do so census data was chosen as data source. In Italy, the largest institution that carries out the official census and statistical surveys is called ISTAT. Its activities include demographic and economic censuses as well as many social, technical, and environmental surveys and analyses at different scales. The results of their investigations can be reached at their online database [23]. To select adequate parameters, PEOPLES framework was followed as a guideline [24]. The first step consisted of creating a list of all indicators obtainable from the ISTAT database. In the second step, indicators were filtered by time, selecting the period ranging from 2007 to 2017. The choice of this time frame was found to be optimal to include the greatest number of parameters since many of them had not been collected prior to 2007 and newer data has not been fully published yet. Among all the available statistical records, only a few are relevant to measure resilience. For this reason, at the end of the data collection and screening process, only 12 annual indicators ranging from 2007 to 2017 could be selected. The further refinement that could be achieved by performing a correlation analysis was not considered necessary due to the already low number of variables, which could lead to misleading results. The list of indicators with a brief description is provided in Table 1.

Despite an exact correspondence to the indicators proposed in PEOPLES framework could not be achieved, the selected indicators can still be considered similar. This similarity is shown in Table 2, which reports a comparison between the available data and the corresponding indicators present in PEOPLES methodology. It can be seen that the available data falls somehow in various categories of PEOPLES framework indicators except for number 12 “people living in damaged houses” which is deemed to be a significant indicator describing the socio-economic status of the population. Besides, Table 2 shows also the slightly different definition of indicators assumed by PEOPLES framework compared to the ones adopted by ISTAT. This confirms that existing methodologies should inevitably be adapted to the specific case. Indeed, they tend to be as comprehensive as possible and for this reason they propose several input parameters. Typically, a larger number of input parameters should lead to a more accurate result. Nonetheless, there is not a clear indication of the minimum number of indicators and whether or how this affects the overall measure. It is also worth noting that multiple indicators are often suggested to better define a single characteristic of the analyzed system. For instance, to define the economic development of a community, indicators such as annual income, median household income, percentage of households covered by insurance, tax revenues, wealthy retirees, etc. could all be used. Therefore, the type and number of indicators can significantly vary depending on the object of the study and its peculiarities. When comparing many of the existing frameworks and methodologies, there is overlapping in some concepts and specific variables. This allows to identify some core categories of indicators [25]. The majority of the overlap concerns social indicators. In our application, the 12 indicators belong to the major and most common categories (i.e., social education, income, health access, community attributes, infrastructures and buildings). Other categories of indicators are more specific such as preparedness, number of religious organizations, number of nonprofit organizations, population covered by hazard mitigation plans, etc. Such indicators are challenging to collect consistently throughout the years on a regional scale. Some of them could also be impossible to define because they refer to aspects that are extraneous to the analyzed community.

Another aspect to take into account is the effect that the single indicator has towards resilience. Depending on the way they are defined, some indicators contribute positively while others have a negative impact. The last column of Table 2 indicates the effect of the indicator on resilience. The letter “P” stands for positive effect, and it is assigned to measures that contribute to increasing resilience, while the letter “N” stands for negative effect, and it is assigned to those that do the converse. For instance, the higher the “elders’ index” the less resilient the region since old people give less contribution to the growth of the community, they are prone to health issues, and unwilling to change their habits.

Table 1. Description of the selected indicators.

No.	Indicator	Description
1	Population density	Percentage of inhabitants per square kilometer
2	Elders’ index	Ratio between elders (more than 65 years old) and young people (less than 14 years old)
3	Number of foreigners	Number of not Italian citizens living in the region
4	People holding a middle school diploma	Population who have attained a middle school diploma (8th grade) as their highest education
5	People holding a degree	Population who have attained a Bachelor’s or Master’s degree
6	Gross domestic product (GDP)	Gross domestic product of each region in million euros
7	Relative poverty index	Ratio between the number of families with a total spending minor or equal to the Italian poverty threshold (defined each year by ISTAT) and the total number of resident families
8	Unemployment rate	Percentage of unemployed people
9	Number of doctors	Number of doctors per 10,000 inhabitants
10	Number of hospital beds	Number of hospital beds per 1,000 inhabitants
11	Families with Internet access	Percentage of families who have access to the Internet

12	People living in damaged houses	Percentage of people who declared to live in damaged buildings

Table 2. Available data compared to PEOPLES' dimensions, components, indicators, and measures.

No.	Selected indicator at regional level	PEOPLES framework indicator	PEOPLES component	PEOPLES framework definition	Indicator effect
1	Population density	Population density	Distribution/Density	Average number of people per area ÷ SV	P
2	Elders' index	Age	Composition	% population whose age is between 18 and 65	N
3	Number of foreigners	Place attachment-not recent immigrants	Composition	% population whose age is between 18 and 65	N
4	People holding a middle school diploma	Educational attainment equality	Socio-Economic Status	% population with college education – % population with less than high school education	P
5	People holding a degree	Educational attainment equality	Socio-Economic Status	% population with college education – % population with less than high school education	P
6	Gross domestic product (GDP)	Income	Socio-Economic Status	Capita household income ÷ SV	P
7	Relative poverty index	Poverty	Socio-Economic Status	% population whose income is below minimum wage	N
8	Unemployment rate	Occupation	Socio-Economic Status	Employment rate %	N
9	Number of doctors	Medical care capacity	Lifelines	Number of hospital beds per population ÷ SV	P
10	Number of hospital beds	Physician access	Lifelines	Number of physicians per population ÷ SV	P
11	Families with Internet access	High-speed internet infrastructure	Lifelines	% population with access to broadband internet service	P
12	People living in damaged houses	-	-	-	N

3. Resilience computation

3.1. Normalization criteria of the indicators

To combine indicators, the first step consists in normalizing them so that they range between 0 and 1. The best normalization criterion would be to divide each measure by an optimal performance value defined by a competent authority or best practices. This value would be essential to provide a benchmark to measure the resilience of a system. In this wat, the system's serviceability at a certain time could be compared to the optimal performance value to know how much serviceability deficiency the system experiences. However, defining or finding references for an optimal value for each indicator could be notably challenging. In this study, indicators were normalized to the best performing region. For example, considering the indicator "GDP", Lombardy is the region with the highest value of gross domestic product. Hence, this value is considered as the optimal performance value to which the GDP of the other regions is normalized.

As previously mentioned, some of the selected indicators have a negative effect on resilience. For those parameters, the complementary value has been calculated. In this specific case, the complementary measure was calculated for the following indicators: elders' index, number of foreigners, relative poverty index, unemployment rate, people living in damaged houses.

3.2. Combination of the indicators

Interdependencies between different indicators can highly affect the result of the resilience assessment. To consider interdependencies, different coefficients are assigned to each variable through an interdependence analysis. The proposed method is based on the construction of an interdependence matrix, as proposed in POEPLES framework [9]. The idea is that a variable highly interdependent on others is likely to have a major effect on the resilience evaluation. Variations of a highly interdependent indicator yield to variations of the indicators dependent on it, affecting the overall resilience index. Each cell in the matrix represents the level of interdependency between two variables. This matrix is a $[n \times n]$ square matrix where n is the number of selected variables. In this study, it is assumed that possible values for the elements in the matrix are *0*, *0.5* or *1*, indicating no dependence, medium dependence, and full dependence, respectively, as expressed in Equation (1):

$$\mathbf{I} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad a_{ii} = \begin{cases} 0 \\ 0.5 \\ 1 \end{cases} \tag{1}$$

where the element a_{ij} represents the dependency of the *i-th* variable to the *j-th* variable. Values can be identified using descriptive knowledge in the form of a questionnaire filled by a group of experts. The expert responsibility is to identify whether two indicators have a "low" or "high" dependence based on their experience. If the number of collected responses is large enough, results can bet treated statistically to better consider uncertainties and reduce subjectivity. For instance, a probability distribution function could be adopted for each variable, and eventually discuss resilience measures in terms of mean and standard deviation.

The interdependency matrix is not symmetrical because if variable i is dependent on variable j, the opposite is not necessarily true. For example, the indicator "GDP" can be regarded as strongly dependent on the "elder's index", whereas the latter has a weak dependence on "GDP".

Once the elements of the matrix are determined, the interdependence vector (λ) is calculated. For the i-th variable, the interdependence factor is obtained by normalizing the sum of the values in the *i-th* column to the maximum value found among all columns' sum. A high value means high dependence of the corresponding variable to the others. The interdependency factor is mathematically calculated as shown in Equation (2):

$$\boldsymbol{\lambda} = \{\lambda_1, \ldots, \lambda_n\},\ n = 1, \ldots, 12$$
$$\lambda_i = \frac{\sum_{j=1}^{n} a_{ji}}{\max\left(\sum_{j=1}^{n} a_{j1}, \ldots, \sum_{j=1}^{n} a_{jn}\right)} \tag{2}$$

It should be noted that the interdependency among variables is greatly related to the community type (e.g. urban, rural, etc.). For instance, indicators related to the economic dimension are significantly less dependent on indicators related to the lifelines dimension in a rural community as opposed to an urban environment. In modern and industrial communities, economic development is the dimension that most other dimensions are dependent on. This implies that after a disaster, for a fast and efficient recovery, most resources should be allocated to lifelines since many parameters are heavily dependent on it. In this work, all regions are analyzed in the same manner. However, if detailed data about the type of regional communities was available, it would be recommended to apply correction factors to take into account this aspect.

Another aspect that should be highlighted is that indicators do not contribute equally to the overall resilience. The importance of variables strictly depends on the type of community. For example, in a rural community, lifestyle and economic indicators have not the same contribution toward the overall community resilience as environment-related parameters. In addition, the relevance of each indicator is dependent on the type of hazard. To include this aspect, each variable is assigned with an importance factor (c) that can assume three values, i.e., 1, 2, or 3, where 1 means low importance, 2 means medium importance, and 3 means high importance (Equation (3)). As for the interdependence matrix, also this factor can be estimated through the evaluation of experts and decision-makers.

$$\mathbf{c} = \{c_1, \ldots, c_n\} \quad c_i = \begin{cases} 1 \\ 2 \\ 3 \end{cases} \tag{3}$$

Importance factors can be estimated for various scenarios. Depending on the context, the same indicators may assume different importance on the calculation of resilience. In this study, three scenarios related to seismic hazard were taken into account. The first consists in the evaluation of global resilience (*Rg*) under normal circumstances, the second represents resilience under seismic emergency conditions (*Re*), and the last corresponds to the assessment of resilience in the restoration phase (*Rr*).

The final weighting factor (w) for each variable is calculated combining both interdependence and importance factors as shown in Equation (4):

$$\mathbf{w} = \{w_1, \ldots, w_n\},\ n = 1, \ldots, 12$$

$$w_i = \frac{\lambda_i \cdot c_i}{\sum_{j=1}^{n} \lambda_j \cdot c_j} \cdot n \tag{4}$$

After obtaining weighting factors for all indicators, the final resilience metric for each region (R_i) is obtained through the aggregation of weighted measures for all indicators (Equation 5).

$$R_i = \frac{\sum_{i=1}^{n} w_i m_i}{n}, \quad n = 12 \tag{5}$$

where m_i is the corresponding normalized measure for the *i-th* indicator.

4. Results

The elements of the interdependence matrix and importance factors were determined by conducting a survey. The group of experts who participated in the survey was composed of 20 people who were asked to fill out questionnaires (see Appendix A). Their age ranges from 30 to 50 and 55% are women. Six of them are doctors working in public hospitals, while the rest of the group works in administrative offices of municipalities and regions. Due to the small size of the poll, only average values of the responses were used instead of treating them statistically.

Table 3 reports the average values obtained for the interdependence matrix and the calculation of the interdependence vector (λ). The results of the survey show that gross domestic product is the most interdependent parameter followed by the elders' index, while the least interdependent indicators are "people living in damaged houses" and "families with Internet access". Table 4 summarizes the average importance factors for normal conditions, emergency, and restoration phase. Results show how the same indicators play different roles depending on the ongoing situation. For example, the gross domestic product turned out to be the most important parameter under normal conditions and among the most important ones during the restoration phase but it is one of the least relevant during a seismic emergency when resources are managed at the country level. On the other hand, the number of doctors and hospital beds are extremely important in the emergency phase, while their impact on resilience during the restoration process is limited.

Table 3. Interdependence matrix.

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	Population density	1.00	0.08	0.03	0.05	0	0.48	0.53	0.15	0	0	0	0.03
2	Elders' index	0.15	1.00	0.05	0.08	0.03	0.50	0.05	0.13	0.08	0.03	0	0
3	Number of foreigners	0.50	0.15	1.00	0.03	0.08	0.45	0.53	0.45	0.03	0	0	0
4	People holding a middle school diploma	0.03	0.88	0.03	1.00	0.10	0.48	0.08	0.08	0.05	0	0.08	0
5	People holding a degree	0.08	0.45	0.03	0.83	1.00	0.50	0.03	0.10	0.03	0.08	0.08	0
6	GDP	0.88	0.50	0.48	0.50	0.43	1.00	0	0.98	0.15	0.15	0.03	0.03
7	Relative poverty index	0.08	0.08	0.13	0.03	0.05	0.50	1.00	0.93	0.03	0	0.08	0.18
8	Unemployment rate	0.43	0.03	0.18	0.53	0.53	0.98	0.03	1.00	0.03	0	0.12	0.08

9	Number of doctors	0.55	0.73	0	0.08	0.08	0.03	0	0.08	1.00	0.65	0	0
10	Number of hospital beds	0.50	0.93	0	0.05	0.03	0.43	0.45	0.13	0.25	1.00	0	0
11	Families with Internet access	0.43	0.53	0.10	0.45	0.98	0.08	0.98	0.50	0	0	1.00	0
12	People living in damaged houses	0.08	0.03	0.18	0.08	0.05	0.48	1.00	0.03	0	0	0.03	1.00
	Interdependence factors	0.80	0.91	0.37	0.63	0.57	1.00	0.79	0.77	0.28	0.32	0.24	0.22

Table 4. Importance factors for normal, emergency, and restoration conditions.

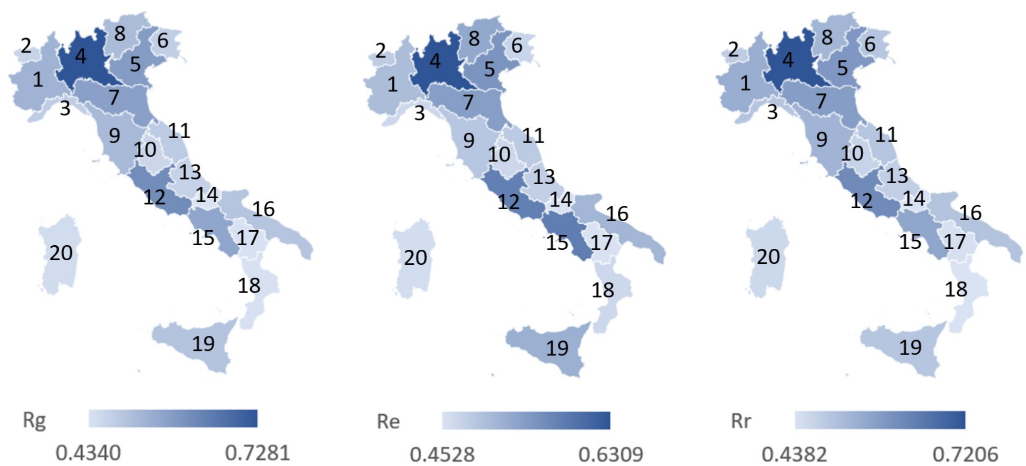
		NORMAL	EMERGENCY	RESTORATION
1	Population density	1.15	1.35	1.30
2	Elders' index	1.95	2.90	1.75
3	Number of foreigners	1.10	1.15	1.15
4	People holding a middle school diploma	1.05	2.00	2.00
5	People holding a degree	1.85	1.75	2.10
6	GDP	2.95	1.25	2.80
7	Relative poverty index	2.00	1.15	2.85
8	Unemployment rate	2.05	1.15	2.85
9	Number of doctors	2.20	3.00	1.30
10	Number of hospital beds	1.85	3.00	1.15
11	Families with Internet access	1.15	1.65	1.05
12	People living in damaged houses	2.25	2.85	1.15

Firstly, the resilience analysis was performed for the 2017 set of data. Weighting factors relative to 2017, calculated using Equation (4), are exemplified in Table 5. The choropleth maps in Figure 1 show the obtained resilience measurement for each region for 2017. This type of visualization allows to rapidly assess and compare regions' performances simply looking at color intensity. From the maps it is evident that Lombardy (region no. 4) is the most resilient region in all three scenarios. Numerical results are reported in Table 6. Looking at these numbers it is possible to further analyze how single regions perform under different circumstances and compare results among different regions. Molise (region no. 14) is the least resilient in both normal and emergency conditions, while Calabria (region no. 18) has the worst performance in the restoration phase.

This analysis, although simplified, already shows some critical aspects. Lombardy proved to be resilient towards seismic events despite in that region seismic hazard is quite low. Conversely, Calabria, as well as many other regions along the Apennines (i.e., the area more subjected to severe earthquakes), showed alarmingly low levels of resilience. Cases in points are the 2009 L'Aquila earthquake and the 2016 Central Italy earthquake. Both events had catastrophic consequences and after many years, in those areas, reconstruction is stuck, and socio-economic activities are still way below pre-event levels. Overall, northern regions seem to be more resilient and this is mostly due to factors such as better economics, lower unemployment rates, and better services. However, some southern regions like Campania and Sicily showed solid performances explained by adequate indicators in terms of younger, dense population and number of doctors. More detailed considerations and comparisons could be made by decision-makers and public administrators through an in-depth analysis of each indicator (see Appendix B).

Table 5. Weighting factors for normal, emergency, and restoration conditions.

		NORMAL	EMERGENCY	RESTORATION
1	Population density	0.85	1.05	0.89
2	Elders' index	1.65	2.59	1.37
3	Number of foreigners	0.38	0.42	0.37
4	People holding a middle school diploma	0.61	1.23	1.07
5	People holding a degree	0.97	0.97	1.02
6	GDP	2.75	1.22	2.40
7	Relative poverty index	1.47	0.89	1.94
8	Unemployment rate	1.47	0.87	1.88
9	Number of doctors	0.57	0.81	0.31
10	Number of hospital beds	0.56	0.95	0.32
11	Families with Internet access	0.26	0.39	0.21
12	People living in damaged houses	0.46	0.62	0.22



(a) (b) (c)

Figure 1. Choropleth maps of Italian regions illustrating (a) global resilience (b) emergency resilience and (c) restoration resilience for 2017 (the numbers identify the regions reported in the first column of Table 6).

To have an idea of the regions' resilience performance over time, the analysis was repeated for each year of the period that goes from 2007 to 2017. The average of the measurements obtained in these years has been used to compare 2017 results. Table 6 summarizes the resilience measures for 2017, those for the 2007-2017 period, and the percentage variation between them. Results point out that most regions decreased their performance over time in all scenarios, with Calabria and Apulia being the worst. The only exceptions are Lombardy, Emilia Romagna, and Trentino South Tyrol which have registered a positive variation in all scenarios.

The obtained results are meant to be used in a preliminary phase of analysis. Regions are not homogeneous in terms of demographics, economics, infrastructures, etc., and those that got a high resilience index might have low resilience territories inside. Undoubtedly, neighborhoods consisting of small, hardly accessible mountain villages are going to be less resilient because of the poorer services and infrastructures. However, in most cases, public funds are distributed at the regional level. Therefore, this type of straightforward resilience analysis could assist decision-makers to significantly improve resource allocation.

Table 6. Values of global, emergency, and restoration resilience for each Italian region.

		2017			2007 – 2017			Variation (%)		
No.	**Region**	**Rg**	**Re**	**Rr**	**Rg**	**Re**	**Rr**	**Rg**	**Re**	**Rr**
1	Piedmont	0.53	0.50	0.54	0.54	0.51	0.55	-1.0	-0.8	-0.7
2	Aosta Valley	0.47	0.48	0.48	0.47	0.48	0.48	0.0	-0.2	0.2
3	Liguria	0.48	0.47	0.50	0.48	0.47	0.50	-0.8	-0.1	-0.7
4	Lombardy	0.73	0.63	0.72	0.73	0.63	0.72	0.1	0.1	0.2
5	Veneto	0.58	0.55	0.59	0.59	0.56	0.59	-0.8	-0.8	-0.7
6	Friuli Venezia Giulia	0.48	0.47	0.50	0.48	0.48	0.50	-1.0	-1.5	-0.6
7	Emilia Romagna	0.57	0.54	0.58	0.57	0.53	0.57	1.2	2.0	1.0
8	Trentino South Tyrol	0.52	0.53	0.53	0.51	0.53	0.52	0.5	0.1	0.5
9	Tuscany	0.52	0.49	0.53	0.52	0.49	0.53	-0.5	-0.1	-0.5
10	Umbria	0.46	0.47	0.47	0.46	0.46	0.48	-0.5	1.1	-1.2
11	Marche	0.48	0.48	0.50	0.49	0.49	0.50	-1.3	-1.1	-1.2
12	Lazio	0.61	0.58	0.61	0.62	0.59	0.62	-1.8	-1.8	-1.2
13	Abruzzo	0.47	0.48	0.48	0.47	0.48	0.48	-1.2	-0.8	-1.2
14	Molise	0.43	0.45	0.44	0.44	0.46	0.45	-2.3	-2.6	-2.4
15	Campania	0.56	0.58	0.56	0.58	0.59	0.58	-2.8	-2.5	-2.7
16	Apulia	0.50	0.51	0.50	0.51	0.53	0.52	-3.1	-3.5	-2.7
17	Basilicata	0.44	0.45	0.44	0.44	0.46	0.44	-0.6	-1.6	0.2
18	Calabria	0.44	0.47	0.44	0.46	0.48	0.46	-4.2	-3.2	-4.7
19	Sicily	0.50	0.52	0.50	0.51	0.53	0.51	-2.8	-1.9	-2.8
20	Sardinia	0.45	0.46	0.46	0.46	0.48	0.49	-2.4	-3.4	-1.7

5. Epidemic risk

The methodology herein presented can be easily extended to other natural or manmade hazards. Epidemics of infectious diseases like the recent Ebola, Severe Acute Respiratory Syndrome (SARS – CoV), Middle East Respiratory Syndrome (MERS – CoV), and the novel Coronavirus (SARS – CoV2) have shown the capacity to seriously affect communities. If we consider biohazard, it is possible to adapt the procedure to estimate the epidemic risk of each Italian region, which is the first step towards resilience assessment. Indeed, limited data from past events and consequences that are different from one disease to another make quantifying epidemic resilience extremely challenging.

The analysis starts with the definition of the epidemic risk, which represents the probability of having human losses due to the spreading of a disease. In the literature, there is no unique definition or approach that the scientific community agrees upon. The World Health Organization decided to follow a composite indicator procedure (INFORM Global Risk Index) developed by the Joint Research Center of European Commission (JRC) [26]. Through this framework, it is possible to calculate a risk index at the country level based on arithmetic and geometric averages of indicators categorized into three dimensions, i.e., hazard and exposure, vulnerability, lack of coping capacity. Similarly, in this work, the epidemic risk is estimated based on the generic definition used also for the seismic risk. According to this definition, the epidemic risk is a combination of three factors, namely hazard, vulnerability, and exposure as shown in Equation (6).

$$E_r = hazard \times vulnerability \times exposure \tag{6}$$

Vulnerability is represented by “the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard” [27]. Given its definition, the concept of vulnerability is quite broad. First, it varies depending on the considered element, i.e., community, system, or asset. Second, vulnerability can be specific to physical, social, economic, and environmental aspects. In addition, vulnerability is hazard dependent. Exposure is represented by the elements that are subject to potential losses due to a hazard. Different hazards may cause damage only to some elements. Therefore, exposed elements are combined with the specific vulnerability to a certain hazard to assess risk. In this case study, the human asset is the one that is vulnerable to biohazard. Since epidemic diseases are directly responsible for human losses, indicators that characterize the human asset, which are of demographic and socio-economic nature, have been considered.

The probabilistic approach commonly used in seismic risk assessment to define the hazard is much more challenging to follow. Biohazard can be of natural, deliberate, or accidental origin and most of the time consequences are unexpected. Moreover, experience is gained through previous outbreak responses which are typically very different from case to case and from country to country. Therefore, the calibration of a probabilistic model based on historical data can be quite challenging if not impossible due to a lack of information.

An indicator-based approach, such as the one previously described, represents a viable alternative at least at a preliminary stage of analysis. Among the twelve indicators used in the resilience analysis, seven have been selected to extend the application of the method to assess the epidemic risk of Italian regions:

- elders’ index;
- relative poverty index;
- number of doctors;
- number of hospital beds;
- population density;
- number of foreigners;
- GDP.

These indicators can positively or negatively affect vulnerability and exposure. It should be noted that both “number of doctors” and “number of hospital beds” tend to reduce vulnerability and therefore their complementary values were used in the analysis. While the interdependence matrix remains the same, new importance factors had to be defined. These were also obtained through a questionnaire averaging the responses (see Appendix A). Table 7 contains all input parameters which are interdependence matrix, interdependence factors, importance factors, and weighting factors. Population density and elders’ index both obtained the highest values in terms of importance and interdependence.

Table 7. Interdependence matrix, importance, and weighting factors of the epidemic risk indicators.

	1	**2**	**3**	**6**	**7**	**9**	**10**	**Importance**	**Weighting**

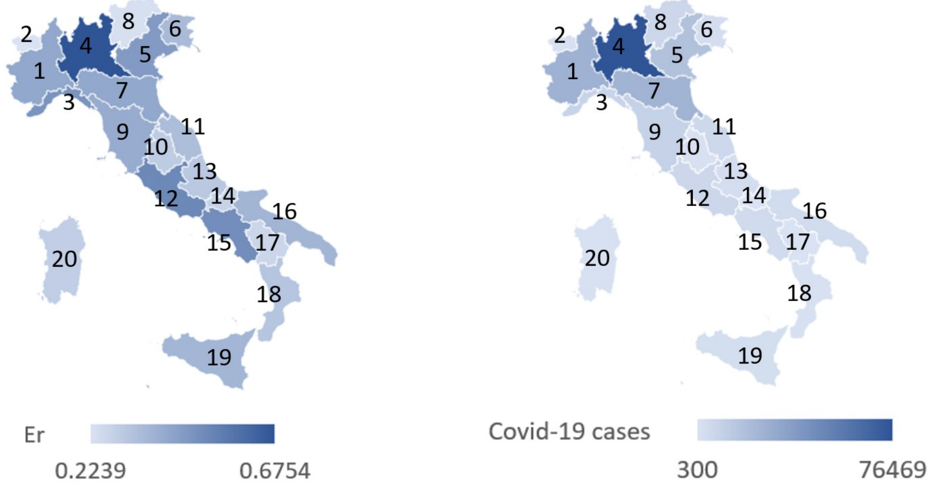
									factor	factor
1	Population density	1.00	0.08	0.03	0.48	0.53	0	0	2.85	2.96
2	Elders' index	0.15	1.00	0.05	0.50	0.05	0.08	0.03	2.95	2.89
3	Number of foreigners	0.50	0.15	1.00	0.45	0.53	0.03	0	1.55	0.74
6	GDP	0.88	0.50	0.48	1.00	0	0.15	0.15	2.25	2.16
7	Relative poverty index	0.08	0.08	0.13	0.50	1.00	0.03	0	2.15	1.56
9	Number of doctors	0.55	0.73	0	0.03	0	1.00	0.65	2.10	0.91
10	Number of hospital beds	0.50	0.93	0	0.43	0.45	0.25	1.00	1.50	0.78
	Interdependence factor	1.00	0.95	0.46	0.93	0.70	0.42	0.50		

Table 8 reports the numerical values representing a measure of the epidemic risk. The analysis was performed in 2017 the results were compared to the average values of the 2007-2017 period. Figure 2a shows the choropleth maps of the epidemic risk for 2017. The regions more at risk are Lombardy and Lazio (region no. 12) due to their high exposure factors, while the ones with the lowest epidemic risk are Aosta Valley (region no. 2) and Trentino South Tyrol (region no. 8). Figure 2b illustrates the choropleth map of the Covid-19 cases registered in each region as of 2020 May 1. Although many other factors should be considered in an accurate evaluation of this epidemic (such as travel and commercial routes to the Asian countries where the virus spread first), the region that was found to have the highest epidemic risk (i.e., Lombardy) is indeed the one with more Covid-19 cases. This demonstrates that the proposed approach can be effective to preliminarily assess the epidemic risk provided that specific indicators are available.

Table 8. Values of epidemic risks for each Italian region.

		2017	**2007 – 2017**	**Variation (%)**
No.	**Region**	**Er**	**Er**	**Er**
1	Piedmont	0.413	0.404	2.3
2	Aosta Valley	0.224	0.215	4.0
3	Liguria	0.474	0.471	0.6
4	Lombardy	0.675	0.661	2.2
5	Veneto	0.452	0.442	2.4
6	Friuli Venezia Giulia	0.351	0.338	3.8
7	Emilia Romagna	0.412	0.413	-0.2
8	Trentino South Tyrol	0.235	0.225	4.3
9	Tuscany	0.399	0.392	1.7
10	Umbria	0.298	0.295	1.1
11	Marche	0.343	0.331	3.6
12	Lazio	0.511	0.484	5.6
13	Abruzzo	0.309	0.297	4.1
14	Molise	0.276	0.257	7.3
15	Campania	0.495	0.476	4.0
16	Apulia	0.371	0.346	7.2
17	Basilicata	0.264	0.250	5.7
18	Calabria	0.318	0.298	6.7

19	Sicily	0.368	0.354	4.0
20	Sardinia	0.290	0.267	8.5



(a) (b)

Figure 2. (a) Choropleth map of Italian regions illustrating epidemic risk for 2017 and (b) number of Covid-19 cases as of 2020 May 1.

6. Conclusions

In this study, an indicator-based approach to measure resilience at the regional level has been presented. When dealing with resilience assessment at large-scale, the main challenge regards data availability. This often results in the inability to thoroughly follow existing resilience frameworks. In the proposed methodology only public census data has been utilized to evaluate the seismic resilience of Italian regions under three circumstances (i.e., normal conditions, seismic emergency, restoration phase). At the end of the data collection process, twelve relevant indicators have been selected and combined using a weighting system derived by questionnaires. The obtained resilience metrics allow to determine the performance of the same region under different scenarios and to make comparisons among different regions. The analysis has been carried on for a ten-year period showing that most regions have decreased their performances. Despite its simplicity, the proposed methodology represents a valid tool for preliminary analyses as it points out solid and poor indicators for each region. This kind of analysis can help decision-makers to deeper investigate community indicators, to allocate the resources to aspects that highly contribute to resilience (both in terms of importance and interdependency), and finally to plan a better recovery process. To demonstrate its versatility, the indicator approach was extended to biohazard aiming at providing a measure of regional epidemic risk. Only seven indicators could be used in this analysis, which affected result accuracy. However, when comparing results with the recent spread of the novel coronavirus, the regions with the highest epidemic risk values were found to be the ones with the highest number of Covid-19 cases.

Appendix A

Figure A.1 shows a sample of the questionnaire used to obtain the interdependence matrix, while Figure A.2 and Figure A.3 show a sample of the questionnaire used to obtain the importance factors for the resilience and epidemic analyses, respectively.

Full Name: ______________________ Title: ______________________

Company: ______________________ Date: ______________________

PART I

Please fill the following table based on your expertise. Each cell represents the level of dependency of one indicator upon the others. Please find the description of each indicator in the following page. Allowed values are **0**, for no dependency, **0.5**, for partial dependency, and **1**, for full dependency.

Indicators	Population density	Elders’ index	Number of foreigners	People holding a middle school diploma	People holding a degree	GDP	Relative poverty index	Unemployment rate	Number of doctors	Number of hospital beds	Families with Internet access	People living in damaged houses
Population density	1											
Elders’ index		1										
Number of foreigners			1									
People holding a middle school diploma				1								
People holding a degree					1							
GDP						1						
Relative poverty index							1					
Unemployment rate								1				
Number of doctors									1			
Number of hospital beds										1		
Families with Internet access											1	
People living in damaged houses												1

Figure A.1. Sample questionnaire used in the survey – interdependence matrix.

PART II

Please fill the following table based on your expertise. Each cell represents the importance of each parameter under normal conditions (NORMAL), during an emergency caused by an earthquake (EMERGENCY), in the restoration phase after an earthquake (RESTORATION). Please find the description of each indicator in the following page. Allowed values are **1**, for low importance, **2**, for moderate importance, and **3**, for high importance.

	NORMAL	EMERGENCY	RESTORATION
Population density			
Elders' index			
Number of foreigners			
People holding a middle school diploma			
People holding a degree			
GDP			
Relative poverty index			
Unemployment rate			
Number of doctors			
Number of hospital beds			
Families with Internet access			
People living in damaged houses			

Figure A.2. Sample questionnaire used in the survey – resilience importance factors.

PART III

Please fill the following table based on your expertise. Each cell represents the importance of each parameter in case of an epidemic. Please find the description of each indicator in the following page. Allowed values are **1**, for low importance, **2**, for moderate importance, and **3**, for high importance.

	EPIDEMIC
Population density	
Elders' index	
Number of foreigners	
GDP	
Relative poverty index	
Number of doctors	
Number of hospital beds	

Figure A.3. Sample questionnaire used in the survey – epidemic importance factors.

Appendix B

Figure B.1 illustrates the choropleth maps of the twelve regional indicators for 2017 used in the resilience analysis.

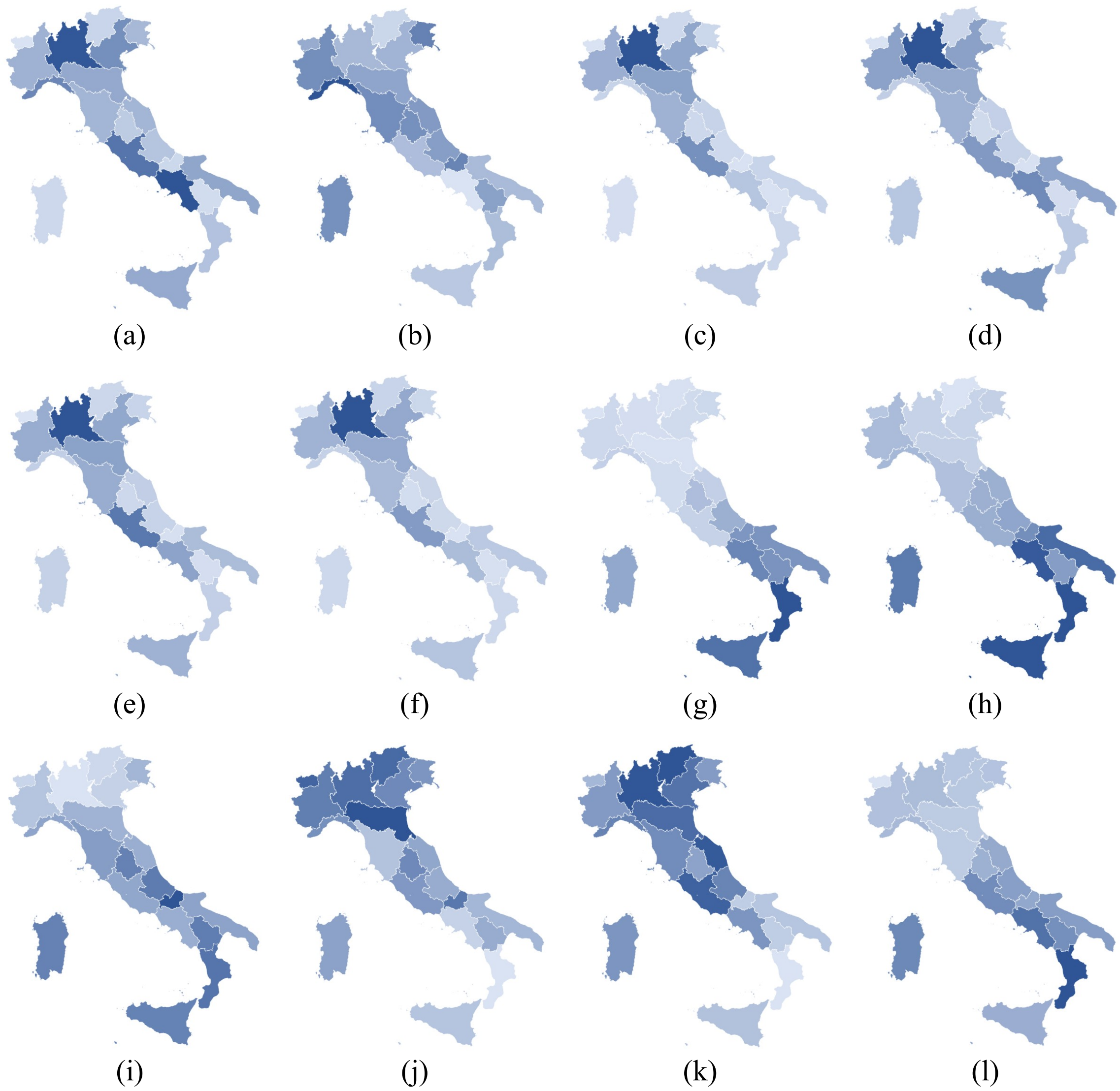


Figure B.1. Choropleth maps for 2017 of (a) population density, (b) elders' index, (c) number of foreigners, (d) people holding a middle school diploma, (e) people holding a degree, (f) GDP, (g) relative poverty index, (h) unemployment rate, (i) number of doctors, (j) number of hospital beds, (k) families with Internet access, and (l) people living in damaged houses.

Acknowledgments

The research leading to these results has received funding from the European Research Council under the Grant Agreement n° ERC_IDEAL RESCUE_637842 of the project IDEAL RESCUE—Integrated Design and Control of Sustainable Communities during Emergencies.

References

[1] S.L. Cutter, K.D. Ash, and C.T. Emrich, The geographies of community disaster resilience, *Global Environmental Change* 29 (2014):65-77.
[2] G.P. Cimellaro, D. Solari, and M. Bruneau, Physical infrastructure Interdependency and regional resilience index after the 2011 Tohoku earthquake in Japan, *Earthquake Engineering & Structural Dynamics* 43 (2014):1763-1784.
[3] O. Kammouh, G. Dervishaj, and G.P. Cimellaro, Quantitative framework to assess resilience and risk at the country level, *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 4 (2018):1-14.
[4] C.S. Renschler, A.E. Frazier, L.A. Arendt, G.P. Cimellaro, A.M. Reinhorn, and M. Bruneau, *A framework for defining and measuring resilience at the community scale: The PEOPLES resilience framework*: MCEER Buffalo, 2010.
[5] S. Marasco, G.P. Cimellaro, A. Cardoni, A. Zamani-Noori, K. Omar, and M. Domaneschi, Integrated platform to assess seismic resilience at the community level, *Sustainable Cities and Society* 64 (2020):https://doi.org/10.1016/j.scs.2020.102506.
[6] UNISDR, Sendai Framework for Disaster Risk Reduction 2015-2030, (2015).
[7] NIST, Disaster Resilience Framework, 75% Draft for San Diego, CA Workshop National Institute of Standards and Technology, 2015.
[8] OSSPAC, The Oregon Resilience Plan: Reducing Risk and Improving Recovery for the Next Cascadia Earthquake and Tsunami, Report to the 77th Legislative Assembly, Salem, Oregon: Oregon Seismic Safety Policy Advisory Commission, 2013.
[9] G.P. Cimellaro, C. Renschler, A.M. Reinhorn, and L. Arendt, PEOPLES: A Framework for Evaluating Resilience, *Journal of Structural Engineering* (2016):04016063.
[10] G.P. Cimellaro, A. Tinebra, C. Renschler, and M. Fragiadakis, New Resilience Index for Urban Water Distribution Networks, *Journal of Structural Engineering* 142 (2016):C4015014.
[11] S.L. Cutter, C.G. Burton, and C.T. Emrich, Disaster resilience indicators for benchmarking baseline conditions, *Journal of Homeland Security and Emergency Management* 7 (2010).
[12] F.H. Norris, S.P. Stevens, B. Pfefferbaum, K.F. Wyche, and R.L. Pfefferbaum, Community Resilience as a Metaphor, *Theory, Set of Capacities* (2008).
[13] J. Twigg, Characteristics of a disaster-resilient community: a guidance note (version 2), (2009).
[14] T. Abeling, N. Huq, D. Chang-Seng, J. Birkmann, J. Wolfertz, F. Renaud, and M. Garschagen, Understanding Disaster Resilience. In *Framing Community Disaster Resilience*: John Wiley & Sons Hoboken NJ and Chichester, West Sussex, 2019, pp. 9-25.
[15] S.E. Chang, and M. Shinozuka, Measuring improvements in the disaster resilience of communities, *Earthquake spectra* 20 (2004):739-755.
[16] M. Bruneau, S.E. Chang, R.T. Eguchi, G.C. Lee, T.D. O'Rourke, A.M. Reinhorn, M. Shinozuka, K. Tierney, W.A. Wallace, and D.v. Winterfeldt, A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities, *Earthquake Spectra* 19 (2003):733-752.

[17] B.M. Ayyub, Practical resilience metrics for planning, design, and decision making, *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 1 (2015):04015008.

[18] X. Liu, E. Ferrario, and E. Zio, Resilience analysis framework for interconnected critical infrastructures, *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering* 3 (2017).

[19] A.A. Saja, A. Goonetilleke, M. Teo, and A.M. Ziyath, A critical review of social resilience assessment frameworks in disaster management, *International journal of disaster risk reduction* (2019):101096.

[20] G.P. Cimellaro, S. Mahin, and M. Domaneschi, Integrating a Human Behavior Model within an Agent-Based Approach for Blasting Evacuation, *Computer-Aided Civil and Infrastructure Engineering* 34 (2019):3-20.

[21] Cimellaro, F. Ozzello, A. Vallero, S. Mahin, and B. Shao, Simulating earthquake evacuation using human behavior models, *Earthquake Engineering & Structural Dynamics* 46 (2017):985-1002.

[22] S. Scherzer, P. Lujala, and J.K. Rød, A community resilience index for Norway: An adaptation of the Baseline Resilience Indicators for Communities (BRIC), *International Journal of Disaster Risk Reduction* 36 (2019):101107.

[23] ISTAT. *Istituto Nazionale di statistica* 2020 [cited. Available from http://dati.istat.it/.

[24] O. Kammouh, A. Zamani Noori, G.P. Cimellaro, and S.A. Mahin, Resilience assessment of urban communities, *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering* 5 (2019):04019002.

[25] S.L. Cutter, The landscape of disaster resilience indicators in the USA, *Natural Hazards* 80 (2016):741-758.

[26] I.E. GRI, and E.I. GRI, Incorporating epidemics risk in the INFORM Global Risk Index, (2018).

[27] U. UNISDR, Terminology on disaster risk reduction, *Geneva, Switzerland* (2009).