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(Article begins on next page)

# Resilience Assessment at The Regional Level Using Census Data

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## 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

47 identify a series of qualitative questions about the presence or absence of certain features and  
48 actions. Each question is associated with a score and the total resilience of the system is  
49 measured by adding all scores. The second group is based on indicators or indices that  
50 provide a quantitative measure of the system's resilience[2]. Indices are representative of  
51 system characteristics and can be statistically evaluated. The overall system resilience is  
52 computed by an aggregation of the selected indexes. The third group is based on the  
53 combination of scorecards and indices providing tools for resilience assessment (such as  
54 guidance, surveys, procedures, or data)[3]. Lastly, the fourth group gathers approaches that  
55 use mathematical models to simulate interactions and relationships within the analyzed  
56 system. Those models can be used to measure various resilience dimensions of the system  
57 (such as physical, social, economic, etc.) through computational simulations [4; 5].

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

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

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

77 A more comprehensive methodology is represented by PEOPLES framework [9], a  
78 multidimensional resilience framework that can be applied from the city level to the country  
79 level. It is also capable of modeling interdependencies among different community layers  
80 [10]. However, it provides a qualitative assessment rather than a quantitative measure.

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

91 The use of indicators is perceived as an important tool to measure the resilience of a  
92 system. Yet developing a standardized set of resilience indicators is challenging for such a  
93 dynamic and context-dependent concept. This is particularly true at the regional and country

94 level. In addition, for such large-scale analyses, data paucity is a common issue that needs to  
95 be overcome.

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

105

## 106 **2. Data collection and selected indicators**

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

120 This paper aims at providing a resilience measure of the 20 regions in which Italy is  
121 divided. To do so census data was chosen as data source. In Italy, the largest institution that  
122 carries out the official census and statistical surveys is called ISTAT. Its activities include  
123 demographic and economic censuses as well as many social, technical, and environmental  
124 surveys and analyses at different scales. The results of their investigations can be reached at  
125 their online database [23]. To select adequate parameters, PEOPLES framework was  
126 followed as a guideline [24]. The first step consisted of creating a list of all indicators  
127 obtainable from the ISTAT database. In the second step, indicators were filtered by time,  
128 selecting the period ranging from 2007 to 2017. The choice of this time frame was found to  
129 be optimal to include the greatest number of parameters since many of them had not been  
130 collected prior to 2007 and newer data has not been fully published yet. Among all the  
131 available statistical records, only a few are relevant to measure resilience. For this reason, at  
132 the end of the data collection and screening process, only 12 annual indicators ranging from  
133 2007 to 2017 could be selected. The further refinement that could be achieved by performing  
134 a correlation analysis was not considered necessary due to the already low number of  
135 variables, which could lead to misleading results. The list of indicators with a brief  
136 description is provided in Table 1.

137 Despite an exact correspondence to the indicators proposed in PEOPLES framework  
138 could not be achieved, the selected indicators can still be considered similar. This similarity is  
139 shown in Table 2, which reports a comparison between the available data and the  
140 corresponding indicators present in PEOPLES methodology. It can be seen that the available  
141 data falls somehow in various categories of PEOPLES framework indicators except for

142 number 12 “people living in damaged houses” which is deemed to be a significant indicator  
 143 describing the socio-economic status of the population. Besides, Table 2 shows also the  
 144 slightly different definition of indicators assumed by PEOPLES framework compared to the  
 145 ones adopted by ISTAT. This confirms that existing methodologies should inevitably be  
 146 adapted to the specific case. Indeed, they tend to be as comprehensive as possible and for this  
 147 reason they propose several input parameters. Typically, a larger number of input parameters  
 148 should lead to a more accurate result. Nonetheless, there is not a clear indication of the  
 149 minimum number of indicators and whether or how this affects the overall measure. It is also  
 150 worth noting that multiple indicators are often suggested to better define a single  
 151 characteristic of the analyzed system. For instance, to define the economic development of a  
 152 community, indicators such as annual income, median household income, percentage of  
 153 households covered by insurance, tax revenues, wealthy retirees, etc. could all be used.  
 154 Therefore, the type and number of indicators can significantly vary depending on the object  
 155 of the study and its peculiarities. When comparing many of the existing frameworks and  
 156 methodologies, there is overlapping in some concepts and specific variables. This allows to  
 157 identify some core categories of indicators [25]. The majority of the overlap concerns social  
 158 indicators. In our application, the 12 indicators belong to the major and most common  
 159 categories (i.e., social education, income, health access, community attributes, infrastructures  
 160 and buildings). Other categories of indicators are more specific such as preparedness, number  
 161 of religious organizations, number of nonprofit organizations, population covered by hazard  
 162 mitigation plans, etc. Such indicators are challenging to collect consistently throughout the  
 163 years on a regional scale. Some of them could also be impossible to define because they refer  
 164 to aspects that are extraneous to the analyzed community.

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

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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 (8 <sup>th</sup> 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
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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

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### 3. Resilience computation

#### 3.1. Normalization criteria of the indicators

183 To combine indicators, the first step consists in normalizing them so that they range between  
 184 0 and 1. The best normalization criterion would be to divide each measure by an optimal  
 185 performance value defined by a competent authority or best practices. This value would be  
 186 essential to provide a benchmark to measure the resilience of a system. In this way, the  
 187 system's serviceability at a certain time could be compared to the optimal performance value  
 188 to know how much serviceability deficiency the system experiences. However, defining or  
 189 finding references for an optimal value for each indicator could be notably challenging. In  
 190 this study, indicators were normalized to the best performing region. For example,  
 191 considering the indicator "GDP", Lombardy is the region with the highest value of gross  
 192 domestic product. Hence, this value is considered as the optimal performance value to which  
 193 the GDP of the other regions is normalized.

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

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### 3.2. Combination of the indicators

201 Interdependencies between different indicators can highly affect the result of the resilience  
 202 assessment. To consider interdependencies, different coefficients are assigned to each  
 203 variable through an interdependence analysis. The proposed method is based on the  
 204 construction of an interdependence matrix, as proposed in POEPLES framework [9]. The  
 205 idea is that a variable highly interdependent on others is likely to have a major effect on the  
 206 resilience evaluation. Variations of a highly interdependent indicator yield to variations of the  
 207 indicators dependent on it, affecting the overall resilience index. Each cell in the matrix  
 208 represents the level of interdependency between two variables. This matrix is a  $[n \times n]$  square  
 209 matrix where  $n$  is the number of selected variables. In this study, it is assumed that possible  
 210 values for the elements in the matrix are 0, 0.5 or 1, indicating no dependence, medium  
 211 dependence, and full dependence, respectively, as expressed in Equation (1):  
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$$\mathbf{I} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad a_{ij} = \begin{cases} 0 \\ 0.5 \\ 1 \end{cases} \quad (1)$$

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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 be 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.

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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".

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Once the elements of the matrix are determined, the interdependence vector ( $\lambda$ ) is calculated. For the  $i$ -th variable, the interdependence factor is obtained by normalizing the

228 sum of the values in the *i*-th column to the maximum value found among all columns' sum. A  
 229 high value means high dependence of the corresponding variable to the others. The  
 230 interdependency factor is mathematically calculated as shown in Equation (2):  
 231

$$\lambda = \{\lambda_1, \dots, \lambda_n\}, n = 1, \dots, 12$$

$$\lambda_i = \frac{\sum_{j=1}^n a_{ji}}{\max\left(\sum_{j=1}^n a_{j1}, \dots, \sum_{j=1}^n a_{jn}\right)} \quad (2)$$

233  
 234 It should be noted that the interdependency among variables is greatly related to the  
 235 community type (e.g. urban, rural, etc.). For instance, indicators related to the economic  
 236 dimension are significantly less dependent on indicators related to the lifelines dimension in a  
 237 rural community as opposed to an urban environment. In modern and industrial communities,  
 238 economic development is the dimension that most other dimensions are dependent on. This  
 239 implies that after a disaster, for a fast and efficient recovery, most resources should be  
 240 allocated to lifelines since many parameters are heavily dependent on it. In this work, all  
 241 regions are analyzed in the same manner. However, if detailed data about the type of regional  
 242 communities was available, it would be recommended to apply correction factors to take into  
 243 account this aspect.

244 Another aspect that should be highlighted is that indicators do not contribute equally to  
 245 the overall resilience. The importance of variables strictly depends on the type of community.  
 246 For example, in a rural community, lifestyle and economic indicators have not the same  
 247 contribution toward the overall community resilience as environment-related parameters. In  
 248 addition, the relevance of each indicator is dependent on the type of hazard. To include this  
 249 aspect, each variable is assigned with an importance factor (*c*) that can assume three values,  
 250 i.e., 1, 2, or 3, where 1 means low importance, 2 means medium importance, and 3 means  
 251 high importance (Equation (3)). As for the interdependence matrix, also this factor can be  
 252 estimated through the evaluation of experts and decision-makers.  
 253

$$\mathbf{c} = \{c_1, \dots, c_n\} \quad c_i = \begin{cases} 1 \\ 2 \\ 3 \end{cases} \quad (3)$$

255  
 256 Importance factors can be estimated for various scenarios. Depending on the context, the  
 257 same indicators may assume different importance on the calculation of resilience. In this  
 258 study, three scenarios related to seismic hazard were taken into account. The first consists in  
 259 the evaluation of global resilience (*Rg*) under normal circumstances, the second represents  
 260 resilience under seismic emergency conditions (*Re*), and the last corresponds to the  
 261 assessment of resilience in the restoration phase (*Rr*).

262 The final weighting factor (*w*) for each variable is calculated combining both  
 263 interdependence and importance factors as shown in Equation (4):  
 264

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

265

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

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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).

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

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

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#### 4. Results

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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.

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Table 3 reports the average values obtained for the interdependence matrix and the calculation of the interdependence vector ( $\lambda$ ). 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.

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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

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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

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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.

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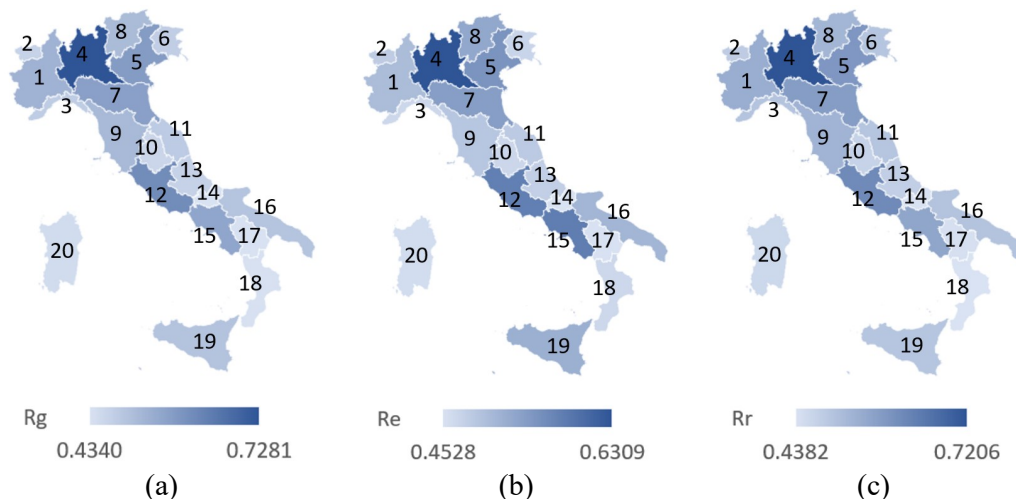
This analysis, although simplified, already shows some critical aspects. Lombardy proved to be resilient towards seismic events despite in that region seismic hazard is quite low. Conversely, Calabria, as well as many other regions along the Apennines (i.e., the area more subjected to severe earthquakes), 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
<b>1</b> Population density	0.85	1.05	0.89
<b>2</b> Elders' index	1.65	2.59	1.37
<b>3</b> Number of foreigners	0.38	0.42	0.37
<b>4</b> People holding a middle school diploma	0.61	1.23	1.07
<b>5</b> People holding a degree	0.97	0.97	1.02
<b>6</b> GDP	2.75	1.22	2.40
<b>7</b> Relative poverty index	1.47	0.89	1.94
<b>8</b> Unemployment rate	1.47	0.87	1.88
<b>9</b> Number of doctors	0.57	0.81	0.31
<b>10</b> Number of hospital beds	0.56	0.95	0.32
<b>11</b> Families with Internet access	0.26	0.39	0.21
<b>12</b> People living in damaged houses	0.46	0.62	0.22

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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).

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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.

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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

342 funds are distributed at the regional level. Therefore, this type of straightforward resilience  
 343 analysis could assist decision-makers to significantly improve resource allocation.  
 344  
 345 Table 6. Values of global, emergency, and restoration resilience for each Italian region.

No.	Region	2017			2007 – 2017			Variation (%)		
		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

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## 5. Epidemic risk

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

357 The analysis starts with the definition of the epidemic risk, which represents the  
 358 probability of having human losses due to the spreading of a disease. In the literature, there is  
 359 no unique definition or approach that the scientific community agrees upon. The World  
 360 Health Organization decided to follow a composite indicator procedure (INFORM Global  
 361 Risk Index) developed by the Joint Research Center of European Commission (JRC) [26].  
 362 Through this framework, it is possible to calculate a risk index at the country level based on  
 363 arithmetic and geometric averages of indicators categorized into three dimensions, i.e.,

364 hazard and exposure, vulnerability, lack of coping capacity. Similarly, in this work, the  
 365 epidemic risk is estimated based on the generic definition used also for the seismic risk.  
 366 According to this definition, the epidemic risk is a combination of three factors, namely  
 367 hazard, vulnerability, and exposure as shown in Equation (6).

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 369 
$$E_r = hazard \times vulnerability \times exposure \quad (6)$$

370  
 371 Vulnerability is represented by “the characteristics and circumstances of a community,  
 372 system or asset that make it susceptible to the damaging effects of a hazard” [27]. Given its  
 373 definition, the concept of vulnerability is quite broad. First, it varies depending on the  
 374 considered element, i.e., community, system, or asset. Second, vulnerability can be specific to  
 375 physical, social, economic, and environmental aspects. In addition, vulnerability is hazard  
 376 dependent. Exposure is represented by the elements that are subject to potential losses due to  
 377 a hazard. Different hazards may cause damage only to some elements. Therefore, exposed  
 378 elements are combined with the specific vulnerability to a certain hazard to assess risk. In this  
 379 case study, the human asset is the one that is vulnerable to biohazard. Since epidemic  
 380 diseases are directly responsible for human losses, indicators that characterize the human  
 381 asset, which are of demographic and socio-economic nature, have been considered.

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

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

- 392 • elders’ index;
- 393 • relative poverty index;
- 394 • number of doctors;
- 395 • number of hospital beds;
- 396 • population density;
- 397 • number of foreigners;
- 398 • GDP.

399 These indicators can positively or negatively affect vulnerability and exposure. It should be  
 400 noted that both “number of doctors” and “number of hospital beds” tend to reduce  
 401 vulnerability and therefore their complementary values were used in the analysis. While the  
 402 interdependence matrix remains the same, new importance factors had to be defined. These  
 403 were also obtained through a questionnaire averaging the responses (see Appendix A). Table  
 404 7 contains all input parameters which are interdependence matrix, interdependence factors,  
 405 importance factors, and weighting factors. Population density and elders’ index both obtained  
 406 the highest values in terms of importance and interdependence.

407  
 408 Table 7. Interdependence matrix, importance, and weighting factors of the epidemic risk  
 409 indicators.

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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		

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411

412 Table 8 reports the numerical values representing a measure of the epidemic risk. The  
413 analysis was performed in 2017 the results were compared to the average values of the 2007-  
414 2017 period. Figure 2a shows the choropleth maps of the epidemic risk for 2017. The regions  
415 more at risk are Lombardy and Lazio (region no. 12) due to their high exposure factors, while  
416 the ones with the lowest epidemic risk are Aosta Valley (region no. 2) and Trentino South  
417 Tyrol (region no. 8). Figure 2b illustrates the choropleth map of the Covid-19 cases registered  
418 in each region as of 2020 May 1. Although many other factors should be considered in an  
419 accurate evaluation of this epidemic (such as travel and commercial routes to the Asian  
420 countries where the virus spread first), the region that was found to have the highest epidemic  
421 risk (i.e., Lombardy) is indeed the one with more Covid-19 cases. This demonstrates that the  
422 proposed approach can be effective to preliminarily assess the epidemic risk provided that  
423 specific indicators are available.

424

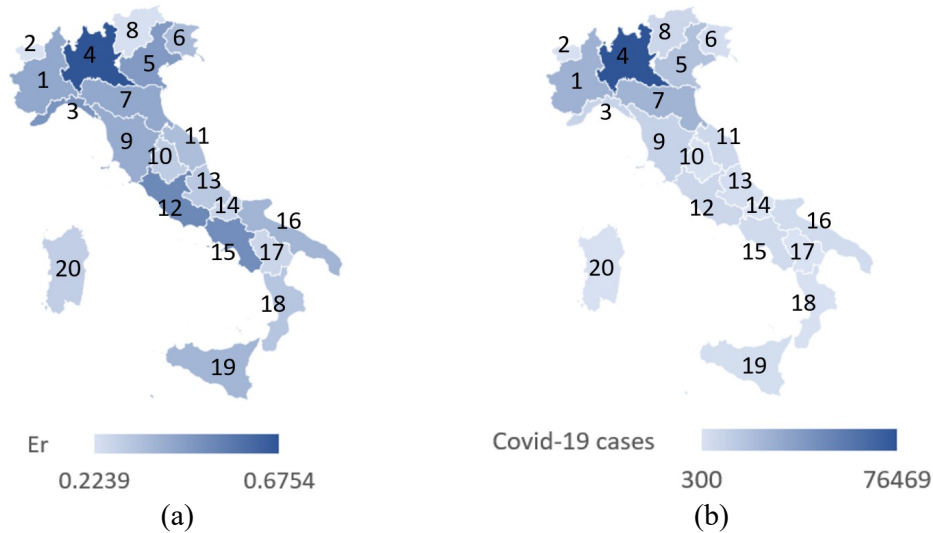
425

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

No.	Region	2017 Er	2007 – 2017 Er	Variation (%) 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

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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.

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## 6. Conclusions

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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.

453 **Appendix A**

454 Figure A.1 shows a sample of the questionnaire used to obtain the interdependence matrix,  
 455 while Figure A.2 and Figure A.3 show a sample of the questionnaire used to obtain the  
 456 importance factors for the resilience and epidemic analyses, respectively.  
 457

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

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

460

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			

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

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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	

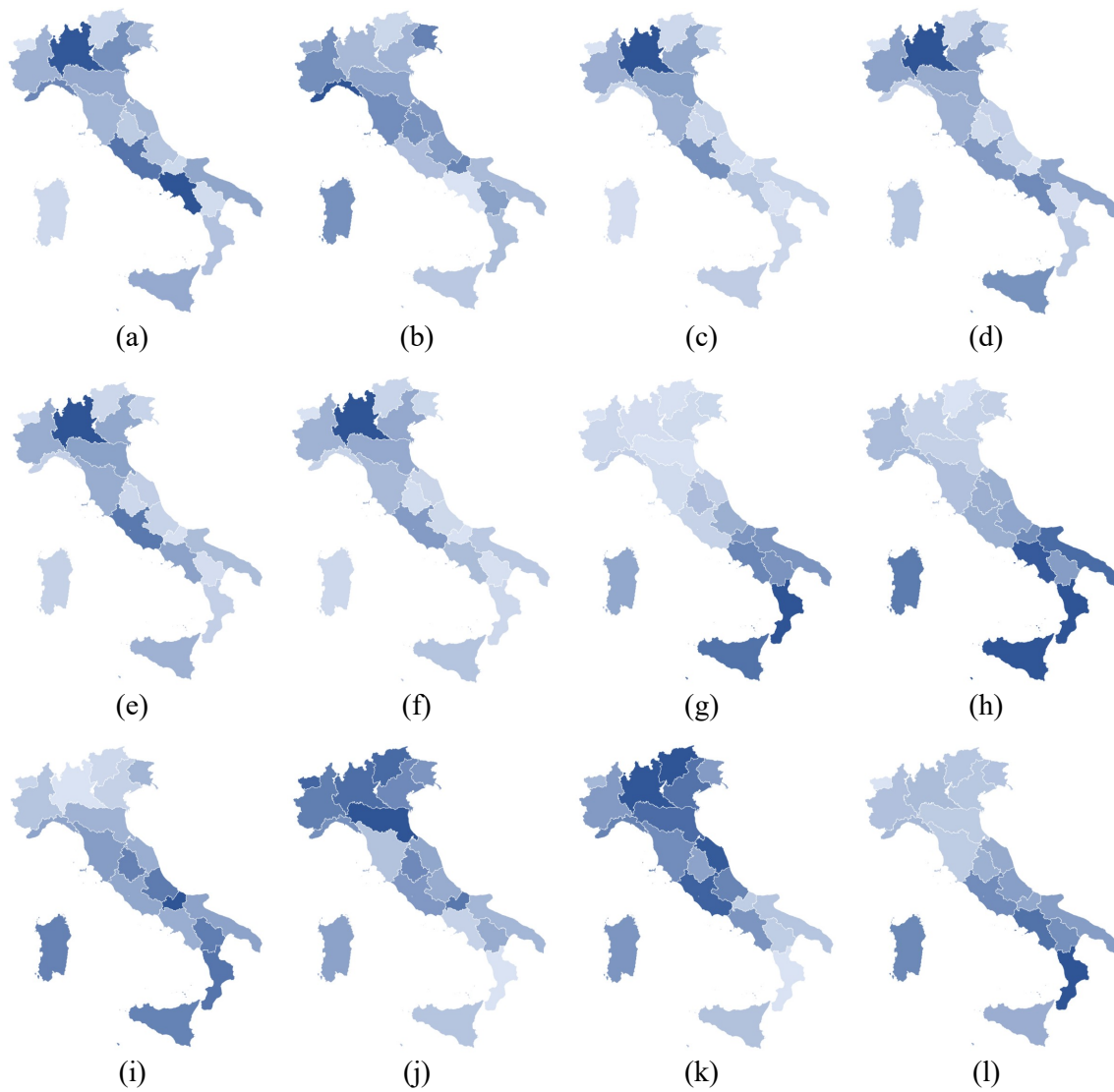
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Figure A.3. Sample questionnaire used in the survey – epidemic importance factors.

466

467 **Appendix B**

468 Figure B.1 illustrates the choropleth maps of the twelve regional indicators for 2017 used in  
469 the resilience analysis.  
470



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

475

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479 IDEAL RESCUE—Integrated Design and Control of Sustainable Communities during  
480 Emergencies.

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