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Resourcefulness quantification approach for resilient communities and countries

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Abstract: Availability of resources is one of the primary criteria for communities to attain a high resilience level during disaster events. This paper introduces a new approach to evaluate resourcefulness at the community and national scales. Resourcefulness is calculated using a proposed composite resourcefulness index, which is a combination of several resourcefulness indicators. To build the resourcefulness index, resourcefulness indicators representing the different aspects of resourcefulness are collected from renowned literary publications. Every indicator is assigned a measure to make it quantifiable. Time-history data for the measures are needed to perform the analysis. While these data could be obtained from different sources, acquiring a full set of data is quite challenging. Hence, to account for missing data, the Multiple Imputation (MI) and the Markov Chain Monte Carlo (MCMC) data imputation methods are adopted. The data are then normalized, assigned weights, and aggregated to obtain the resourcefulness index. A case study is performed to demonstrate the applicability of the approach. The resourcefulness indexes of two countries, namely the United States and Italy, are evaluated. Results show that resourceful communities/countries are more resilient during disaster events as they have more tools to come up with solutions. It is also shown that knowing the current resourcefulness level helps in better identifying what aspects should be improved.

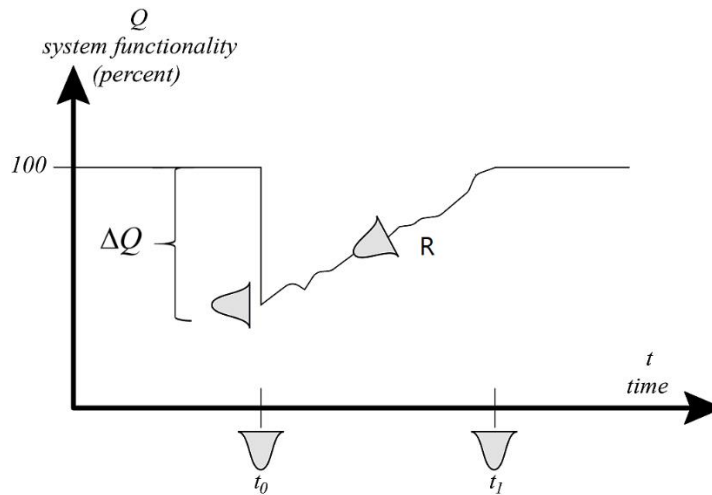
keywords: resilience, resourcefulness, recovery, natural hazards, disaster, community resilience.

27 **1. Introduction**

28 Research on disaster resilience has recently been fostered due to the noticeable increase in the number of
29 natural hazards and human-caused disasters (Cimellaro et al. 2016a; Cimellaro et al. 2016b; Cimellaro et al.
30 2015; De Iuliis et al. 2019b; Kammouh et al. 2018b; Sarkis et al. 2018). During disasters, resilient communities
31 tend to suffer fewer consequences and recover faster than non-resilient communities given the same hazard
32 intensity (Kammouh et al. 2018a; Marasco et al. 2018). This highlights the importance of resilience
33 quantification tools. Several methodologies and frameworks to evaluate and enhance the resilience of regions
34 affected by extremely disruptive events have been proposed by numerous researchers (De Iuliis et al. 2019b;
35 De Iuliis et al. under review; Kammouh et al. 2017; Kammouh et al. 2018f; Zamani Noori et al. 2017).

36 Figure 1 presents a conceptual definition of resilience, introduced by Bruneau et al. (2003). In the figure,
37 the functionality (Q) of a system ranges from 0% to 100%, where 100% and 0% imply full availability and
38 unavailability of services, respectively. A system can be defined as a group of components that jointly deliver
39 a service or a group of services. Therefore, a community can be considered as a system of systems as it is
40 composed of physical and social systems (Kammouh et al. 2018c). The occurrence of a disaster at time t_0
41 causes damage to the system, and this produces an instant drop in the system's functionality (ΔQ) (Kammouh
42 et al. 2018e). Afterward, the system is restored to its initial state over the recovery period ($t_1 - t_0$) with a
43 restoration rate R . Theoretically, resilience is defined as the ability to “prepare, absorb, recover from actual or
44 potential adverse events” (NRC 2015). From the definition, resilience deals not only with already occurring
45 disaster events but also with potential events that may occur in the future. Therefore, resilience quantification
46 cannot be based solely on deterministic studies but should be expressed in a probabilistic manner. For example,
47 as shown in Figure 1, every component of resilience (i.e., ΔQ , t_0 , t_1 , R) may have a certain probability
48 distribution (Cimellaro et al. 2010b). The resilience function in the figure is, therefore, the function
49 corresponding to the mean value of every resilience parameter.

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Figure 1: Measuring the seismic resilience considering uncertainties

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According to Bruneau et al. (2003), there are four characteristics of resilience (also called the 4-Rs):

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- **Redundancy:** refers to the community's ability to provide alternative options for effective and efficient management of emergency situations;

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- **Robustness:** refers to the system's ability to withstand a certain level of stress and consequently preserve its functionality;

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- **Rapidity:** refers to the rate at which the community attain at least its pre-event functionality level;

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- **Resourcefulness:** is the community's "capacity to identify problems, establish priorities, and mobilize resources when the existing conditions threaten to disrupt some elements, systems, or other units of analysis".

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The resilience characteristics are graphically represented in Figure 2. For *redundancy*, the damage of one system does not prevent the functionality of the whole network if the network is redundant. For example, if one hospital is severely damaged, the functionality of another hospital can preserve the functionality of the whole hospital network as people can go to the functioning hospital (Cimellaro et al. 2017a; Cimellaro et al. 2018; Cimellaro et al. 2011). For *robustness*, robust systems can resist high damage using their inherent structural characteristics. For *rapidity*, rapidly restored systems are characterized by higher resilience because they return to their initial state quickly. Finally, for *resourcefulness*, more resources allow the damaged system to recover quickly given that efficient restoration plans are put in place.

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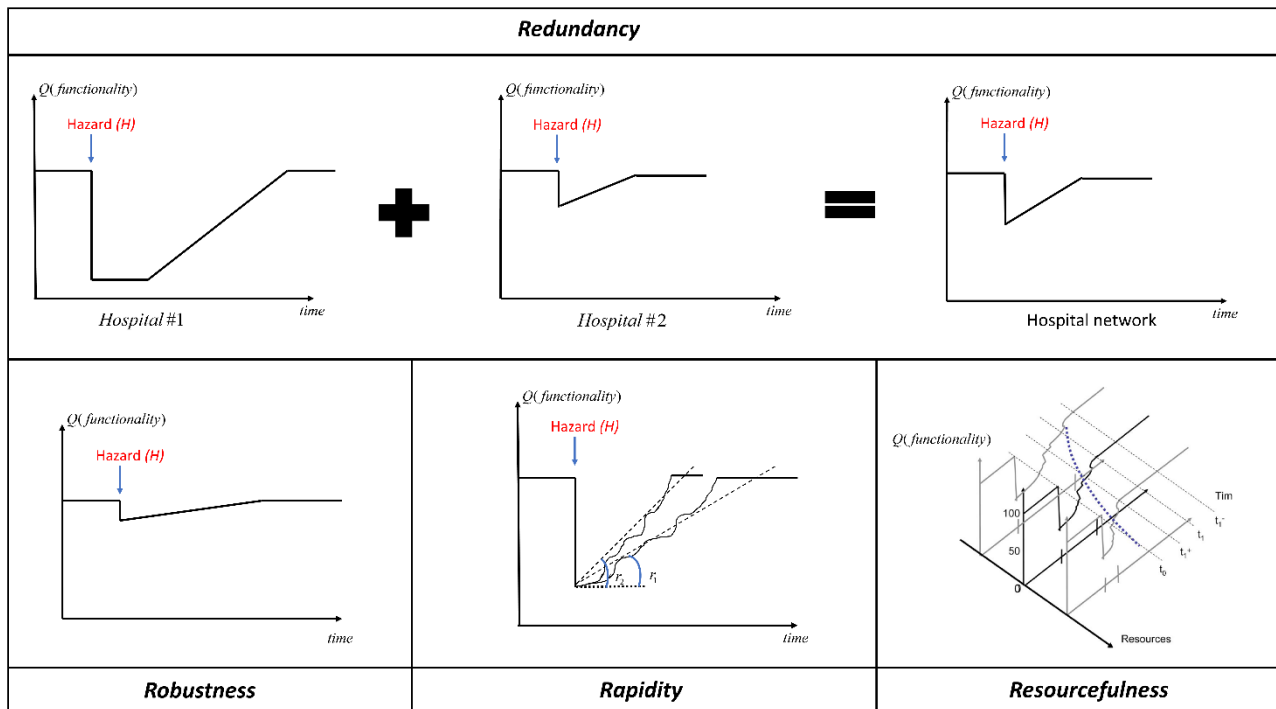


Figure 2: Visual representation of the resilience characteristics

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Resourcefulness assessment is deemed key for enhancing community resilience (Cimellaro et al. 2014; Drabek 2003; Kammouh et al. 2019a; Perrow 2011; Tierney 2008) (Cimellaro et al. 2016c) (De Iuliis et al. 2019a). For instance, if decision-makers are fully aware of the consequences of disaster events as well as the resources that they have to deal with such events, they would be more likely to know how to act and what types of resources to mobilize during the emergency and recovery phases. This, in turn, enhances the emergency response of the community, and thus its resilience. There have been very few studies tackling the concept of resourcefulness in the literature. None of these has attempted to assess the resourcefulness from a quantitative perspective. Thus, this paper introduces a new approach to quantify the resourcefulness of communities using an indicator-based approach. In the context of this work, a community is defined as a geographical area that includes all components needed to sustain life for a group of people (e.g., infrastructure, social systems, etc.). Examples of communities could be a city, a county, or a district. A country, for instance, can be considered as a community that is composed of several smaller communities. Therefore, there are no upper-bound limitations in terms of population number or geographical size.

The proposed framework provides useful guidelines for policymakers to enhance the resilience of communities and countries by identifying the weaknesses in their current plans. The rest of the paper is organized as follows. Section 2 is dedicated to exploring the concept of resourcefulness and introducing its principles. Section 3

88 introduces a methodology to quantify the resourcefulness at the community and national levels. Section 4
 89 presents a case study to illustrate the applicability of the methodology. Finally, conclusions are given in Section
 90 5 together with the proposed future work.

91 **2. Resourcefulness definition and principles**

92 **2.1. Resourcefulness definition**

93 The concept of resourcefulness during disasters has been introduced in the field of emergency management
 94 with a special emphasis on human factors (Cimellaro et al. 2019; Cimellaro et al. 2017b). Several case studies
 95 on emergency management during natural hazards have revealed the importance of resourcefulness in dealing
 96 with such incidents (Cimellaro et al. 2010a; Podolny and Page 1998; Rosenthal et al. 2001). Some researchers
 97 consider resourcefulness as the only factor defining resilience (MacKinnon and Derickson 2013) while others
 98 treat resourcefulness as one of several resilience dimensions (Bruneau et al. 2003; Kammouh et al. 2019a).

99 The term *resourcefulness* has been defined differently in the literature. The most dominant definitions are
 100 summarized in Table 1. The existence of different definitions has made it essential to establish a universal
 101 definition for resourcefulness. Thus, for this study, resourcefulness is defined as the capacity to identify
 102 problems, establish priorities, allocate and mobilize resources before, during, and after an event that may
 103 disrupt elements, systems, or other units of analysis taking into account human factors.

104 Table 1 Resourcefulness definitions

	Resilience dimensions	Definition of Resourcefulness
(Bruneau et al. 2003)	<ul style="list-style-type: none"> - Robustness - Rapidity - Redundancy - Resourcefulness 	“Capacity to identify problems, establish priorities and mobilize resources when conditions exist that threaten to disrupt some element, system, or another unit of analysis.”
NIAC (2009)	<ul style="list-style-type: none"> - Robustness - Resourcefulness 	“Ability to skillfully prepare for, respond to, and manage a crisis or disruption as it unfolds.”

	- Rapid recovery	
(Berkeley et al. 2010)	- Robustness - Resourcefulness - Rapid recovery - Adaptability	“Ability to skillfully manage a disaster as it unfolds. It includes identifying options, prioritizing what should be done both to control damage and to begin mitigating it and communicating decisions to the people who will implement them. Resourcefulness depends primarily on people, not technology.”
(Brown 2015)	- Resistance - Rootedness - Resourcefulness	“Resourcefulness encompasses the resources that people can draw on, but also the capacity to use them at the right time, in the right way.”

105

106 **2.2. Resourcefulness principles**

107 The mathematical boundaries and conditions of resourcefulness are defined herein to ensure they represent the
 108 conceptual definition of resourcefulness. The least possible value for Resourcefulness in this study is 0. This
 109 implies that a community/country can never have less than the absolute absence of resources. On the other
 110 hand, it is improper to set an upper limit for resourcefulness because it is always possible to increase the inflow
 111 of resources. Therefore, resourcefulness (*RFS*) ranges from 0 to $+\infty$:

112
$$RFS \in [0, +\infty] \tag{1}$$

113 Generally, the response of a region in terms of recovery to hazardous events improves gradually. A region
 114 with high resourcefulness would be able to respond better to a disaster. Therefore, adding resources means
 115 enhancing *RFS*. Consequently, if we have a graph in which a resource *x* is plotted against resourcefulness, the
 116 slope would be monotonically increasing:

117
$$RFS(x_2 > x_1) > RFS(x_1) \tag{2}$$

118 Finally, the resourcefulness of a region is independent of the resourcefulness of other regions. Therefore, The
 119 sets of *RFC_c* are statistically independent:

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$$RFS_c \neq f(RFS_{d \neq c}) \quad (3)$$

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3. Methodology

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Resourcefulness does not depend only on the “active” capacity of the people or skills that can be taught and learned, but also on their way of interacting. It is generally challenging to quantify the resourcefulness of a community/country as it involves several distinct characteristics (Kammouh et al. in press). In this work, a quantitative composite index accounting for these characteristics is formulated. The composite index is divided into dimensions and indicators to be able to consider more details in the analysis. Four dimensions are proposed by the authors to represent the different aspects of resourcefulness. Introducing these dimensions helps in structuring the methodology and make it more systematic. This categorization, however, has no effect on the data analysis that will be introduced later in the paper. The dimensions of resourcefulness are:

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- **Political-economic:** support provided by the economic and political structure to the emergency management system;
- **Preparedness:** disaster preparedness of the individual citizens as well as the whole community/country;
- **Trust:** the ability of a community/country to cope with natural hazards as a cohesive unit, tapping into its trust resources;
- **Creativity:** the ability of a community/country to take smart and not obvious decisions during the emergency, which can mitigate losses.

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Every dimension is divided into several indicators and every indicator is assigned a measure to make it quantifiable. The list of dimensions, indicators, and measures with their sources is shown in Table 2. The indicators and measures have been collected from renowned literary publications and then filtered for the purpose of obtaining mutually exclusive indicators. This has necessitated rejecting a number of indicators either because they are not relevant or because they overlapped with other indicators. In every source provided, the corresponding indicator was introduced as an important indicator for resourcefulness; thus, it has been adopted in this paper.

Table 2 Dimensions and indicators subdivision of the resourcefulness framework.

Dim.	Indicator	Symbol	Measure	Source
Political-economic	Economic Complexity	<i>ECI</i>	<i>Economic Complexity Index</i> ÷ <i>TV</i>	(Cutter et al. 2006)
	Bureaucracy Flexibility	<i>BF</i>	<i>Economic Freedom Index</i> ÷ <i>TV</i>	(Ballano 2017)
	Fragility	<i>FSI</i>	<i>(Fragile States Index)</i> ⁻¹ ÷ <i>TV</i>	(Nel and Righarts 2008)
	Mitigation Spending	<i>MS</i>	% <i>GDP allocated by the community to cope with disasters</i> ÷ <i>TV</i>	(Council 2005)
	Safety Rate/Crime rate	<i>SR</i>	<i>(Reported violent crime rate per 100,000 people)</i> ⁻¹ ÷ <i>TV</i>	(Yates and Mackenzie 2018)
	Participation in public life	<i>PPL</i>	% <i>turn-out at last presidential election</i>	(Organization 2002)
Preparedness	Smartphone penetration	<i>S</i>	% <i>population having and using a smartphone</i>	(Palen et al. 2010)
	Disaster Preparedness	<i>FDP</i>	% <i>population reporting having a family emergency plan</i>	(Paton and Johnston 2017)
	Emergency Kit Preparedness	<i>EKP</i>	% <i>population reporting having adequate emergency kits</i>	American Red Cross (2018)
Trust	Safety Perception	<i>SP</i>	% <i>population thinking crime is less than the previous year</i>	(Nogami 2015)
	Volunteering	<i>V</i>	<i>Average volunteering hours per week</i> ÷ <i>TV</i>	(Whittaker et al. 2015)
	Interpersonal Trust	<i>IT</i>	% <i>population thinking others can be trusted</i>	(Carlin et al. 2014)
	Trust in the political system	<i>TPS</i>	% <i>population thinking government can be trusted</i>	(Carlin et al. 2014)
	Trust in the police	<i>TP</i>	% <i>population thinking police can be trusted</i>	(Carlin et al. 2014)
	Patriotism	<i>P</i>	% <i>population proud to belong to the community</i>	(Lee and Loh 2003)
Creativity	Patent applications	<i>PAT</i>	<i>Patent applications per 1,000 people</i> ÷ <i>TV</i>	(Kreps 1990)
	Research and development expenditure	<i>RDE</i>	% <i>GDP invested in research and development</i> ÷ <i>TV</i>	(Kreps 1990)

146 Note: *TV* (target value) represents the optimum value for the given indicator

147 According to the specifications set out by the OECD (Commission 2008), the construction of a composite
 148 index must follow the following steps:

149 1. Defining the index principles;

- 150 2. Data selection;
- 151 3. Imputation of missing data;
- 152 4. Normalization;
- 153 5. Weight allocation;
- 154 6. Aggregation;
- 155 7. Uncertainty and sensitivity analysis.

156 Since the index principles have been defined in the previous section, the next section deals with data selection
157 and imputation.

158 **3.1. Data selection and imputation**

159 The proposed approach uses time-history data for its execution. Practically, it is difficult to obtain a complete
160 statistical data set to perform a resourcefulness analysis. Thus, it is necessary to deal with the issue of missing
161 data. Missing data are data needed for the execution of the methodology but are not available in any of the
162 data sources. For this reason, data imputation has been implemented to account for the missing data. Before
163 choosing the imputation method, missing data patterns should first be analyzed. According to OECD
164 (Commission 2008), there are three main patterns for missing data:

- 165 - *Missing completely at random (MCAR)*: the missingness on the variable is completely unsystematic.
166 For example, when data are missing for respondents for which their questionnaire was lost in the mail.
167 In this case, missing values do not depend on the observed variable or any other variables in the data
168 set;
- 169 - *Missing at random (MAR)*: missing values do not depend on the observed variable but on other
170 variables;
- 171 - *Not missing at random (NMAR)*: when the missing values on a variable are related to the values of that
172 variable itself, even after controlling for other variables.

173 The MCAR or MAR are the most common types of missing data patterns, and imputation methods can only
174 handle these types of missing data.

175 To minimize the influence of the data on the results, the following categories are excluded from the analysis:

- 176 1. Indicators with more than 75% of missing data over the time steps considered (e.g. years);
177 2. Time steps with more than 50% of missing data.

178 Missing data imputation is done as follows:

- 179 1. $x_i - x_j$ is plotted, where x_i and x_j are two variables.
180 2. R^2 of each plot is computed, where R is a unitless quantity ranging between 0 and 1 representing the
181 reliability of a predicting model in modeling a set starting raw data:

182
$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (4)$$

183 where y_i is the vertical coordinate of generic point i , \hat{y}_i is the vertical coordinate of the corresponding point
184 in the prediction model (i.e. Regression line), \bar{y} is the mean value of all y_i .

- 185 3. If $R^2 \geq 0.5$, then x_j is considered a good regressor for x_i .
186 4. The Multiple Imputation (MI) technique is used for imputing missing data whose indicators have at least
187 one good regressor while the Markov Chain Monte Carlo (MCMC) imputation method is used for
188 imputing missing data whose indicators have no good regressors.

189 **3.2. Normalization**

190 The measurement units differ among the indicators. Thus, it is important to normalize the data to transform
191 their measurement units into pure and dimensionless numbers. Moreover, some indicators have a positive
192 influence on the dimensions while others have negative effects. This needs to be considered in the approach.

193 To ensure a successful normalization of data, a potentially suitable approach is to choose an external value
194 known as *Target Value* (Balbi et al. 2018; Cutter et al. 2010; Kammouh et al. 2018d). This value serves as a
195 normalizing benchmark and is considered an optimum value for the given indicator. Every indicator must have
196 an optimal value TV and that value must be properly chosen. The same normalization method has been adopted
197 in the PEOPLES framework (Kammouh and Cimellaro 2018; Kammouh et al. 2019b), which is a hierarchical
198 framework for assessing the resilience of communities at different scales. It comprises seven dimensions,

199 summarized by the acronym PEOPLES, which stands for population, environmental and ecosystem, organized
200 governmental services, physical infrastructures, lifestyle, economic development, and social capital. In their
201 case, however, each normalized indicator cannot be higher than 1. Therefore, 1 is used in place of x/TV
202 whenever the indicator x is higher than TV .

203 To ensure a successful implementation of the selected weighting method, it is necessary to perform the Z-
204 scores transformation. This technique transforms a data set with variance σ^2 and mean μ to a set with variance
205 1 and mean equal to 0. The Z-scores method transforms the data as follows:

$$206 \quad x_y^* = \frac{x_y - \mu(x)}{\sigma(x)} \quad (5)$$

207 **3.3. Weights allocation**

208 A weight is assigned to each normalized indicator. It is a measure of the indicator's contribution to the overall
209 resourcefulness index. The PEOPLES framework allocates weights based on an interdependency matrix,
210 which is filled out by an expert (or a group of experts) (Kammouh et al. 2019b). The expert assigns 1 if he/she
211 thinks that the indicator in the row depends on the indicator in the column. Then, an interdependency factor
212 for every indicator is derived. The essence is to "prevent possible overlap among the indicators" (Kammouh
213 et al. 2019b). If this overlap is not removed, the final composite index may be affected. Nevertheless, the
214 expert-based method used in PEOPLES framework appears not to be suitable in our case due to the following
215 reasons:

- 216 1. Indicators in PEOPLES framework are mainly statistical data representing tangible dimensions. It is
217 possible to select one or more experts to evaluate the interdependency among indicators. For example,
218 an economist could have an authoritative opinion regarding the interdependency between *income* and
219 *occupation*, or an environmental scientist between *air quality* and *water quality*. For the resourcefulness
220 index, however, it is not possible to follow the same procedure as the indicators are not straightforward
221 in terms of quantification.
- 222 2. Resourcefulness is an inherent feature of communities and it must not change if people's opinions
223 change.

224 Due to the above reasons, a data-driven method was chosen for this study. The primary objective is to assign
 225 low weights to indicators that correlate highly with others because they share information with other indicators
 226 and high weights to indicators that do not correlate with others. The most suitable methodological approach
 227 for this study is the Principal Components Analysis (PCA).

228 The Principal Components Analysis is a multivariate technique that is typically used “to explain the variance
 229 of the observed data through a few linear combinations of the original data” (Commission 2008). It was first
 230 proposed by Pearson (1901) and then developed by Hotelling (1933). This methodology requires a sufficient
 231 number of events to be reliable. Different rules of thumb have been proposed in different studies and all of
 232 them are based on the events/variables ratio: 10:1 (Commission 2008), 5:1 (Bryant and Yarnold 1995), *etc.*

233 In this method, the variations of the variables (indicators) x_1, x_2, \dots, x_N are explained by another set of variables
 234 Y_1, Y_2, \dots, Y_N , called Principal Components, which are mutually uncorrelated (*i.e.* orthogonal) (Eq. (6)). These
 235 two sets of variables are of linear combination but are not correlated (Eq. (7)), where a_{ij} are coefficients that
 236 can be computed.

$$237 \quad \text{cov}(Y_i, Y_j) = 0 \quad (6)$$

$$238 \quad \begin{aligned} Y_1 &= a_{11}x_1 + a_{12}x_2 + \dots + a_{1N}x_N \\ Y_2 &= a_{21}x_1 + a_{22}x_2 + \dots + a_{2N}x_N \\ &\dots \\ Y_Q &= a_{Q1}x_1 + a_{Q2}x_2 + \dots + a_{QN}x_N \end{aligned} \quad (7)$$

239 $Y_{Q+1}, Y_{Q+2}, \dots, Y_N$ do not offer any meaningful contribution to the cumulative variance and are therefore
 240 ignored.

241 The aim of this method is to select Q and to compute the *component loadings* a_{ij} . The first step is to calculate
 242 the covariance matrix S , where S is symmetric because $s_{ij} = s_{ji}$:

$$243 \quad S = \begin{bmatrix} s_{11} & \dots & s_{1N} \\ \vdots & \ddots & \vdots \\ s_{N1} & \dots & s_{NN} \end{bmatrix} \quad (8)$$

244 where

245
$$s_{ij} = \text{COV}(x_i, x_j) \quad (9)$$

246 If the starting data x_N are standardized (*i.e.* normalized by means of z-scores method), then S should be
 247 considered equal to the Correlation Matrix (P), which is a matrix whose coefficients represent the correlation
 248 among the indicators (Pearson 1895). In this case, if the correlation between two indicators is high, then the
 249 indicators contain mutual information.

250
$$P = \begin{bmatrix} \rho_{11} & \cdots & \rho_{1N} \\ \vdots & \ddots & \vdots \\ \rho_{N1} & \cdots & \rho_{NN} \end{bmatrix} \quad (10)$$

251 where ρ_{ij} is the Pearson's correlation coefficient, computed as follows:

252
$$\rho_{ij} = \text{corr}(x_i, x_j) = \frac{\text{COV}(x_i, x_j)}{\sigma_{x_i} \sigma_{x_j}} \quad (11)$$

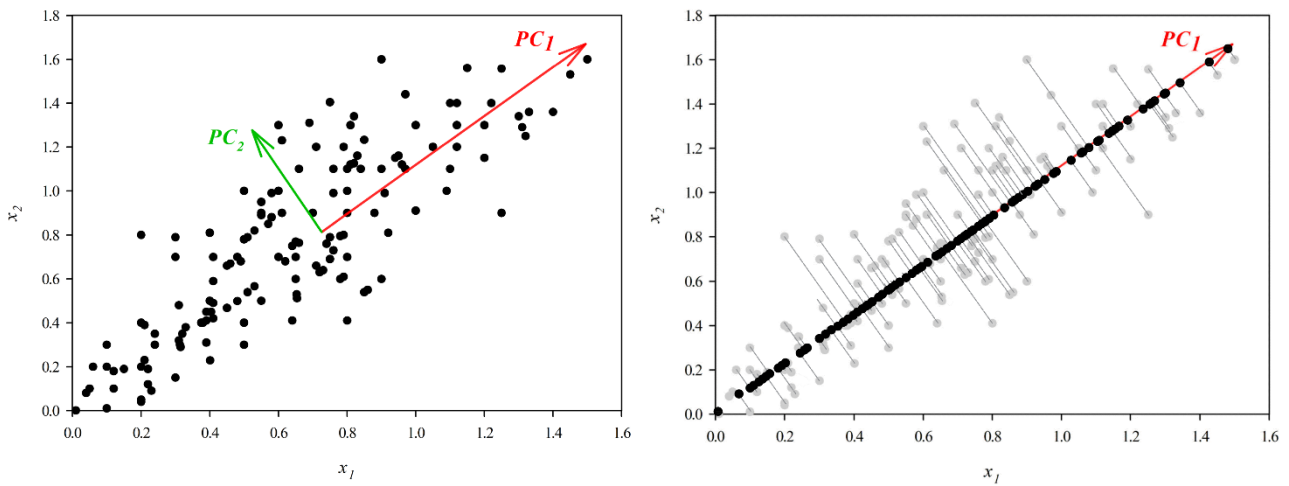
253 The eigenvalues λ and eigenvectors d are computed and organized in a vector $[\lambda]$ and matrix $[D]$, respectively.
 254 For each eigenvalue, the solution of $\det(P - \lambda I) = 0$ represents the percentage of variance (of the original
 255 data). The eigenvectors are arranged in decreasing order. Such an arrangement makes it possible to select a
 256 group whose cumulative variance is sufficient to represent the original data with no excessive information loss.
 257 Once selected, each eigenvector is multiplied by the square root of the corresponding eigenvalue to obtain the
 258 *Component Loadings Matrix A*.

259 Each of the principal components has a geometric meaning. For the sake of simplicity, let's assume that x_1
 260 and x_2 , two variables in the R^2 space, are the only two variables involved in the statistical analysis. Under
 261 such an assumption, data involving all candidates (*i.e.* communities, countries, etc.) can be represented as
 262 depicted in Figure 3a. However, it is important to note that the same assumption must be extended to the R^n
 263 space. The vector, which is the first principal component, can be identified and consequently modified to
 264 minimize the sum of the squared distances points-vector. This will also result in the maximization of their
 265 variance (*i.e.* the eigenvalues of P). Since the space is 2-dimensional, it is necessary to include a second
 266 principal component, which is orthogonal to the first and explain the remaining variance. These principal
 267 components are indicated using vectors, representing the geometric meaning of eigenvectors of matrix P .

268 The higher is the variance explained by the first principal component, the lower is the information loss if the
 269 second component is neglected. For example, if the second principal component was neglected, the data
 270 distribution would be treated as the main available data, where every point is projected on the first principal
 271 component. A visual representation of this relationship is shown in Figure 3b. Finally, the weights w_i are
 272 evaluated using Eq. (12).

$$273 \quad w_i = \frac{\sum_{i=1}^N \sum_{j=1}^Q D_{ij}^2 \cdot \lambda_j}{\sum_{j=1}^Q D_{ij}^2 \cdot \lambda_j} \quad (12)$$

274 It is important to note that different communities/countries may obtain different weights to the same indicator
 275 (i.e., the principle of independence among communities/countries). In addition, the weight of the same
 276 indicator may change every year due to the refinement process. The greater is the number of events (i.e. years),
 277 the higher is the analysis' reliability.



278
 279 **Figure 3:** (a) Hypothetical data distribution and principal components, (b) Selection of the first principal
 280 component.

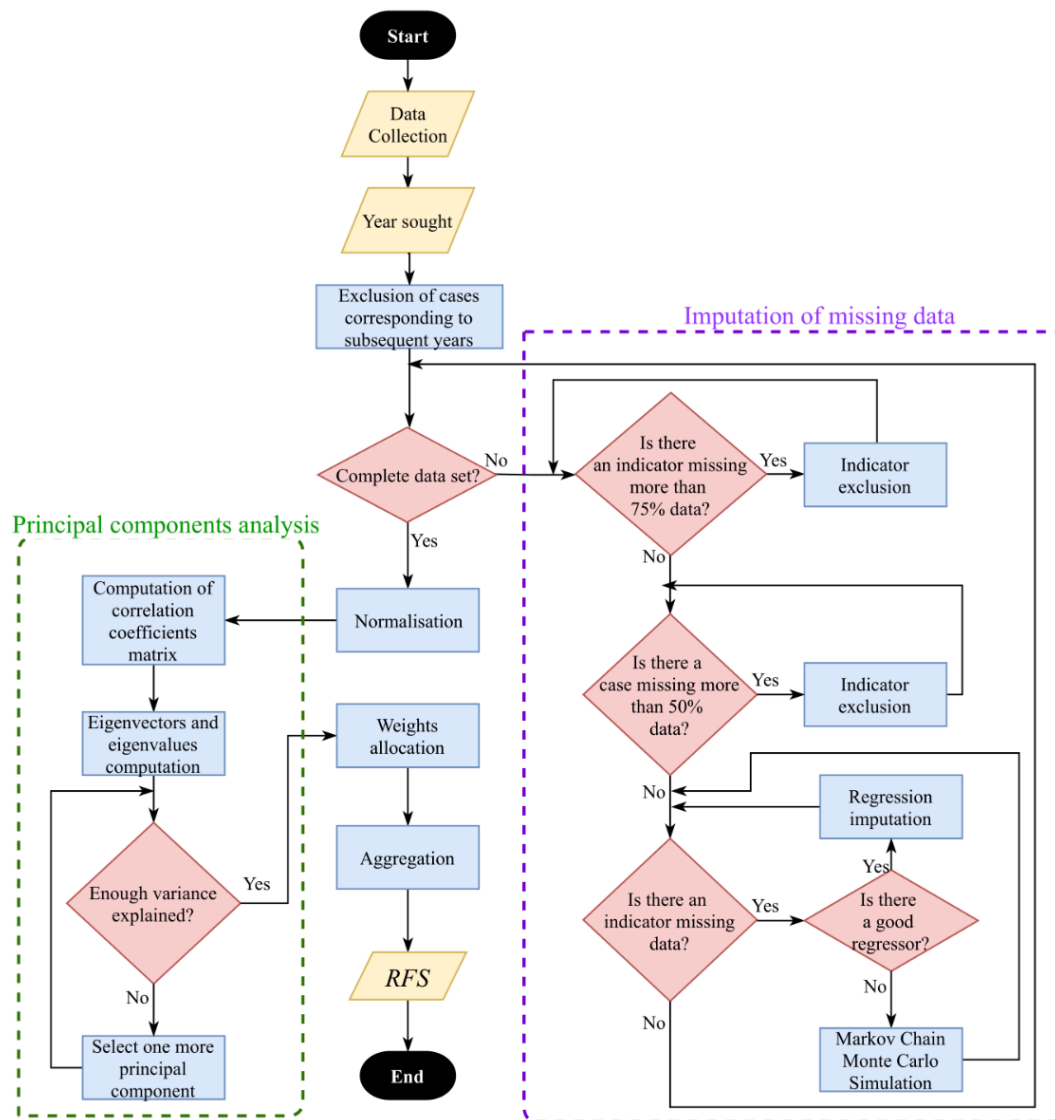
281 **3.4. Aggregating indicators**

282 The last step of the methodology is the selection of an aggregation technique. There are two main methods
 283 that have been proposed in the literature: Additive aggregation and Geometric aggregation (Commission
 284 2008). The additive aggregation method allows full compensability among indicators, whereas the geometric
 285 method partially prevents compensability. For example, Paton and Johnston (2017) investigated the
 286 contribution of the *Hakka spirit* to the response of the Taiwanese community in the aftermath of an earthquake

287 that took place in 1999. The term *Hakkas* refers to Han Chinese, who migrated to other countries including
288 Taiwan. The specific approach they usually adopt in response to natural hazards is termed “the spirit of the
289 sturdy neck”. This statement simply means holding on firmly in the face of extreme adversity. The term can
290 also mean “to keep on doing something without any regard to your strength”. According to the authors, this
291 mindset was instrumental to the quick recovery of Tung Shih town after the earthquake. On its part, the
292 government responded quickly, even though its progress was limited by the inadequacy of essential materials
293 and the city’s unpreparedness. Nevertheless, the *Hakka spirit* effectively mitigated the impacts of this lack of
294 preparedness, and this supports the additive aggregation since the absence of some resources did not prevent
295 responding to the disaster. Therefore, Additive aggregation is the most suitable aggregation method for
296 computing the resourcefulness composite index because it allows compensability among indicators.
297 Mathematically, the additive aggregation is represented as follows:

$$298 \quad RFS_{c,y} = \sum_{i=1}^Q x_{yj} \cdot w_j \quad (13)$$

299 where $RFS_{c,y}$ is the resourcefulness index of region c in year y . The flow chart of the proposed methodology is
300 shown in Figure 4. The algorithm can be automated using any programming language or even spreadsheets.



301
302 **Figure 4:** Flow chart of the resourcefulness assessment methodology

303 **4. Case study: resourcefulness index of the USA and Italy**

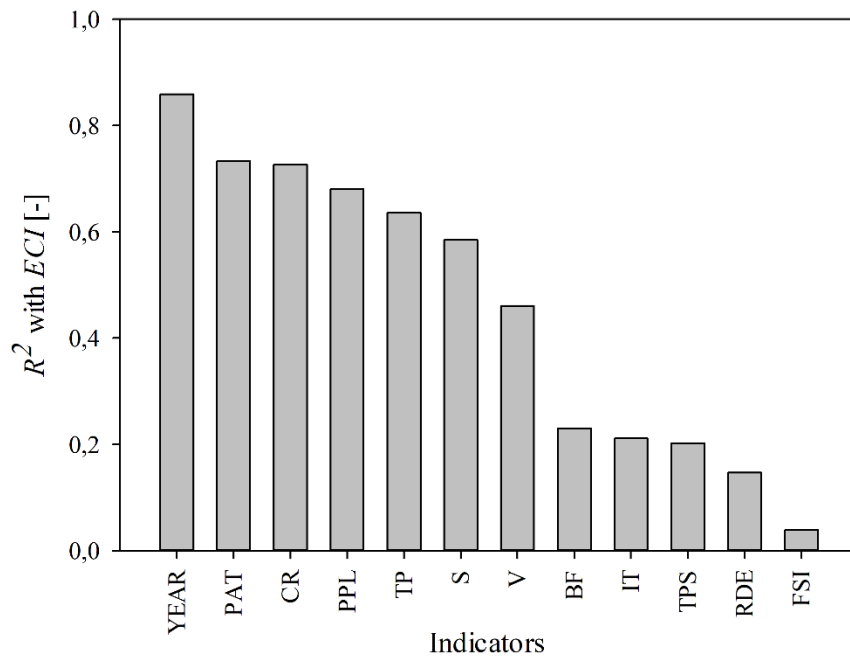
304 In this section, the proposed methodology is applied to evaluate resourcefulness on the national scale.
 305 Countries for which enough data can be found are selected because data availability is essential for the analysis.
 306 The first country of choice for this study is the United States. A preliminary study on the country has revealed
 307 that it has the highest number of available and retrievable data. Analysis of a second case study is necessary
 308 for validation. In this case, Italy was chosen for this purpose. The list of sources used for the compilation of
 309 data is presented in the Appendix.

311 **4.1 Imputation of missing data**

312 Out of the total amount of data needed, only 29.4% and 18.3% of data were found for the United States and
313 Italy, respectively. Some indicators were also excluded because no associated data was available. For instance,
314 the analysis of the United States did not include the *Mitigation Spending* indicator. On the other hand, five
315 indicators were excluded in the analysis of Italy, namely *Mitigation Spending*, *Safety Perception*, *Family*
316 *Disaster Preparedness*, *Emergency Kit Preparedness*, and *Patriotism*. Excluded indicators are highlighted in
317 the Appendix with the notion (n/a). Thus, the data set matrix $[X]$ is a 28×16 matrix for the USA and 18×12
318 matrix for Italy.

319 The next step involves the selection of good regressors for each indicator. Figure 5 shows an example of the
320 R^2 results between an indicator (i.e., *ECI*) and the other indicators for Italy. In the analysis, we also consider
321 the year as an indicator although it is not a resourcefulness indicator. Results show that *YEAR* is the best
322 regressor for *ECI*, with $R^2 = 0.85$. To extend the analysis to all other indicators, Figure 6 shows the R^2 values
323 between each indicator and the other indicators, of both the USA and Italy. Each symbol represents the R^2
324 value between the corresponding indicator on the x-axis the indicator represented by the symbol. If the symbol
325 lies above the threshold line ($R^2 = 0.5$), the indicator represented by the symbol is considered a good regressor
326 for the indicator on the x-axis; otherwise, it is not considered as a good regressor. Good regressors couldn't be
327 obtained for some indicators, namely *Bureaucracy Flexibility* and *Fragile States Index* for USA and
328 *Interpersonal Trus* for Italy. Consequently, MCMC simulations have been carried out by using the software

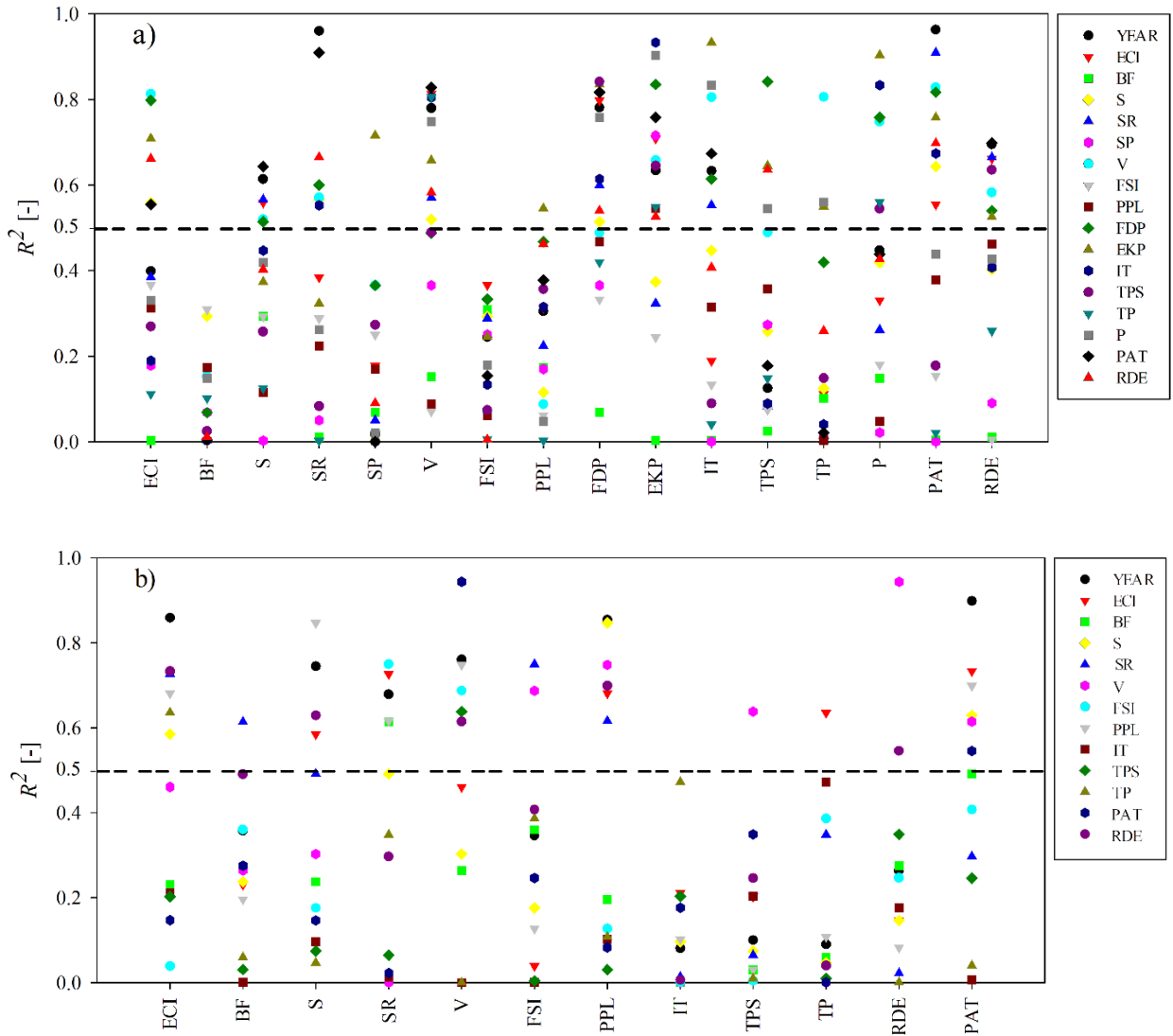
329 SPSS (IBM-Corp) to impute missing data of these indicators. The software takes as input the initial data set
330 and returns a complete set with no missing data.



331

332

Figure 5: Selection of regressors for the indicator *Economic Complexity ECI for Italy*



333 **Figure 6:** Selection of good regressors for each indicator for (a) the USA and (b) Italy

334 **4.2 Results**

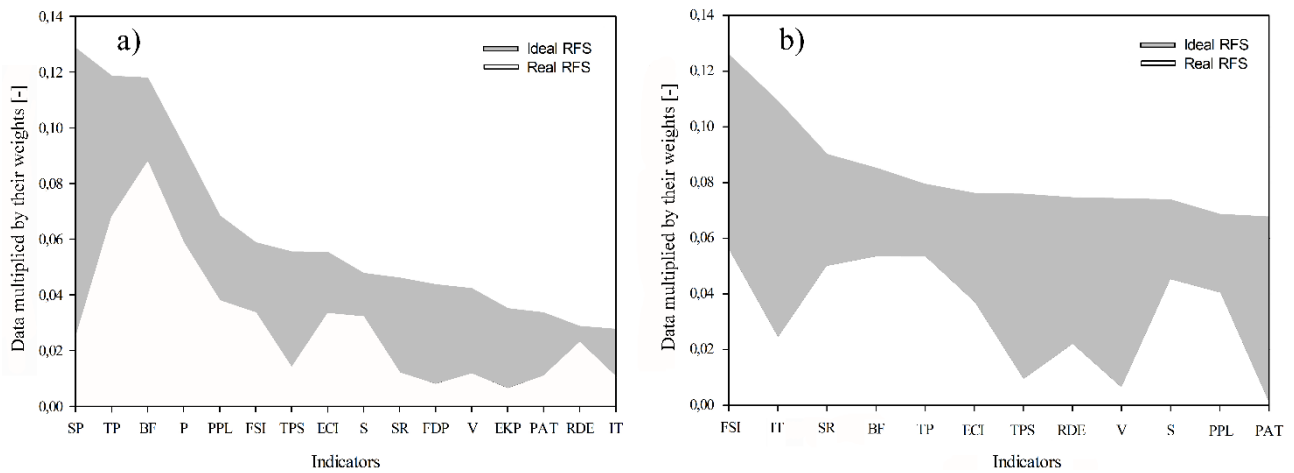
335 *4.2.1 Resourcefulness results*

336 Following the imputation of data, data is normalized, weighted, and aggregated using the methodology
 337 introduced before. The outputs of the analysis for the US and Italy for the year 2017, which is the last year of
 338 the analysis, are given in Eqs. (14) and (15) respectively:

339
$$RFS_{USA,2017} = 0.4605 \quad (14)$$

340
$$RFS_{ITA,2017} = 0.3954 \quad (15)$$

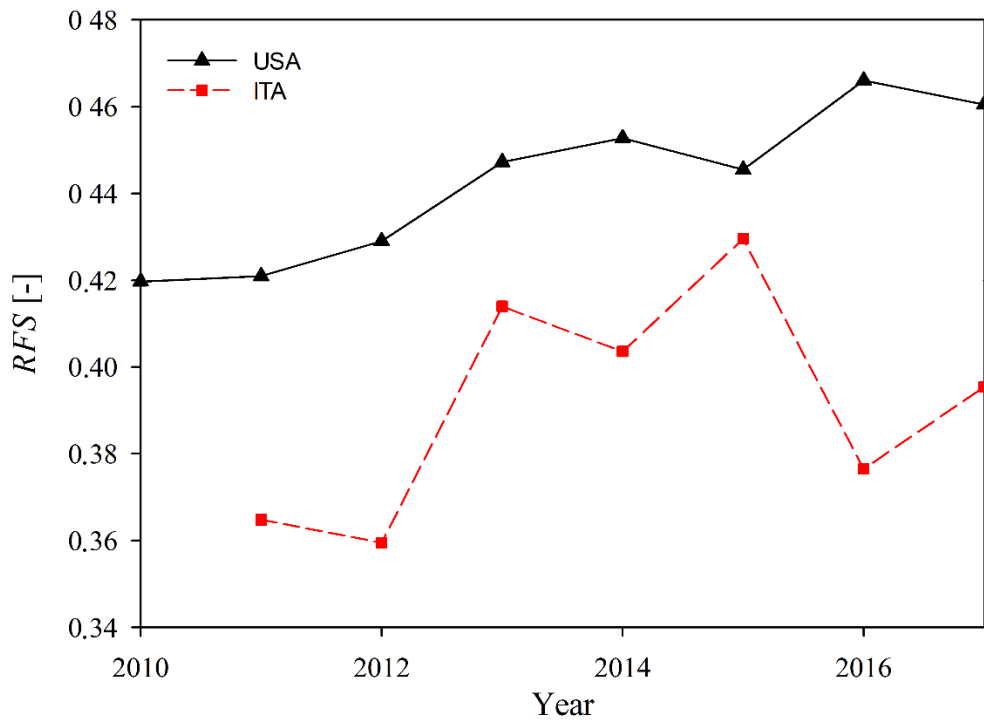
341 Figure 7 illustrates the indicators values for both the USA and Italy. Real data are plotted in white whereas
 342 grey refers to the ideal values. The entire area (grey and white) is equal to 1 (i.e. 100%, ideal *RFS*), whereas
 343 the white-colored area is equal to 0.4605 for the USA (i.e. 46.05%, real *RFS*_{USA,2017}) and 0.3954 for Italy (i.e.
 344 39.54%, real *RFS*_{ITA,2017}). It is important to note that the ideal value is not the maximum, but the value that
 345 corresponds to the perfect community/country whose indicators are equal to the *Target Values* multiplied by
 346 the corresponding weights. Therefore, perfect communities/countries would have a grey area equal to zero.



347
 348 **Figure 7:** (a) USA's *RFS* and (b) Italy's *RFS*

349 It is possible to monitor the evolution of the indicators as well as the consistency between the *RFS*'s over the
 350 years. However, it is necessary to first determine the years that have enough and accurate data required for the
 351 successful computation of *RFS*. As already described above, the Principal Components Analysis should have
 352 at its disposal enough events (years) to return precise outputs. Nevertheless, none of the already defined criteria
 353 are satisfied as $[X]_{USA}$ matrix is 28×16 , with a events/variables ratio equal to 1.75 and $[X]_{ITA}$ is 18×12 ,
 354 with an events/variables ratio equal to 1.50. Thus, the results in this study are certainly affected by the lack of
 355 data related to some years.

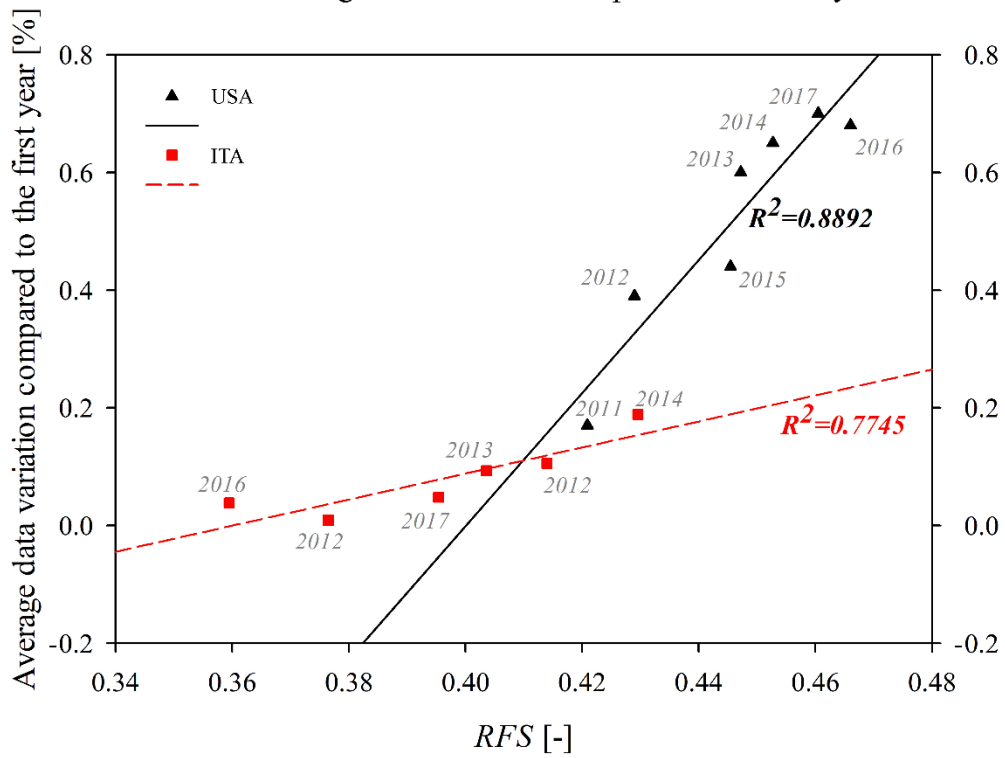
356 It is preferable to ignore the *RFS* of the USA and Italy for the years 2010 and 2011 respectively since data for
 357 these years are not available. Further analysis for the USA will be restricted to between 2010 and 2017, while
 358 that of Italy will be limited to between 2011 and 2017. The *RFS* of the USA between 2010 and 2017 and that
 359 of Italy between 2011 and 2017 are shown in Figure 8. In addition, the relationship between the *RFS* and the
 360 average data variation for the first year of analysis is shown in Figure 9.



362

363

Figure 8: Evolution of *RFS* over the years of the USA and Italy



364

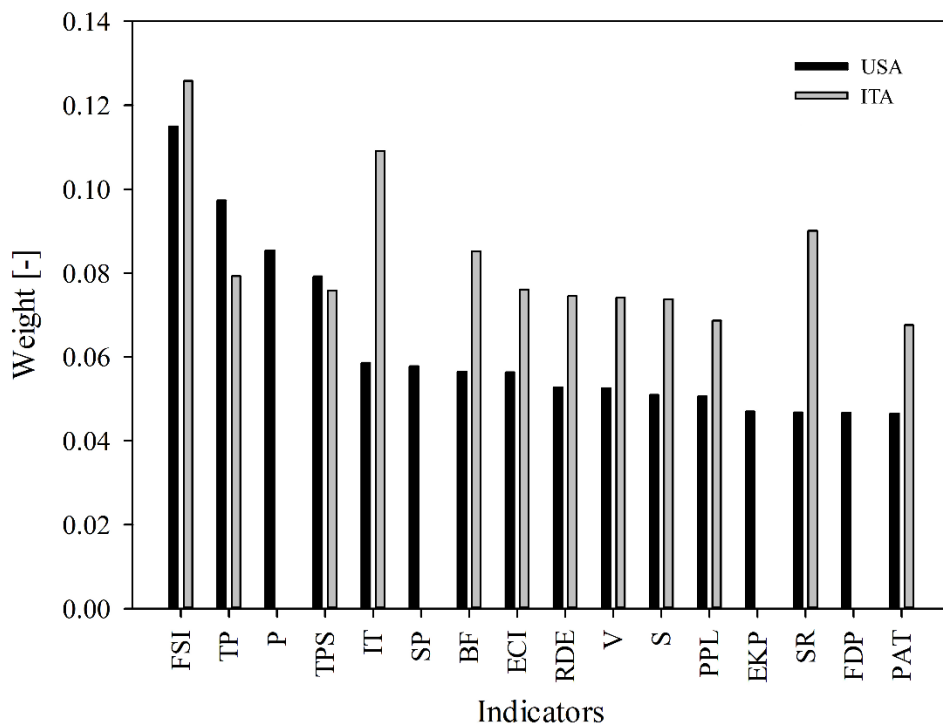
365

Figure 9: *RFS* over the years vs percentage average data variation compared to the first year

366 4.2.2 Weights results

367 The most crucial step of the algorithm is the allocation of weights. Weights assignment is the most debatable
368 topic when dealing with indicators. The weights generated by the analysis carried out for the year 2017 are
369 shown in Figure 10. The fact that the weights change every year implies that they are subject to a process of
370 refinement. It seems reasonable to expect a high weights variation in the first years, which then decreases
371 progressively with time. This is confirmed in Figure 11 where the weight variation of both the US and Italy is
372 decreasing. However, the decrease in weight variation in the case of Italy is very slow. This can be attributed
373 to several reasons, for instance:

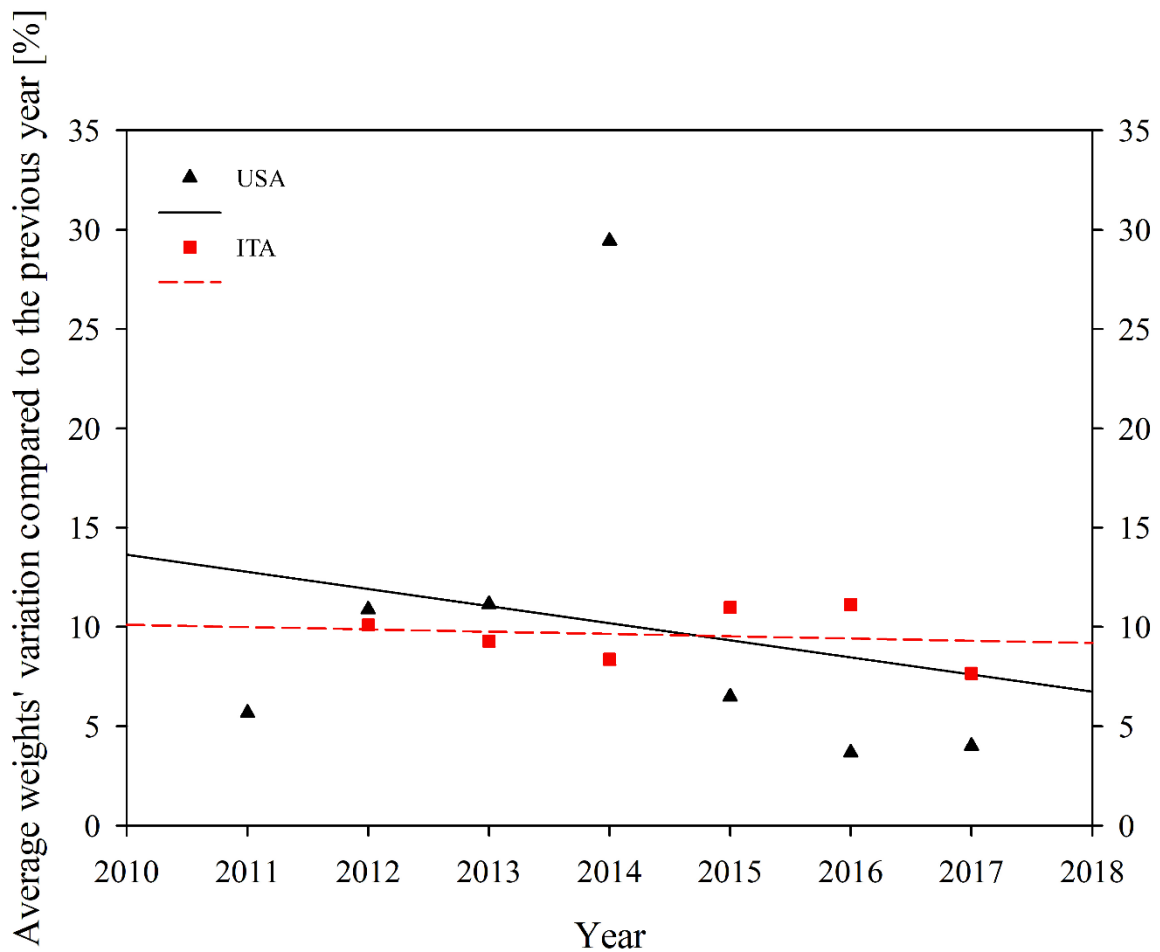
- 374 1. The criterion used to select the number of principal components for Italy resulted in four principal
375 components in 2011 while only three principal components from 2013 on;
- 376 2. As observed above, none of the events/variables ratios suggested by OECD are satisfied. This is because
377 the analysis may have been affected by the low number of events (*i.e.* years).
- 378 3. The initial data matrix for Italy was only 18.3% filled.



379

380

Figure 10: 2017 weights for Italy and the United States



381

382

Figure 11: Years vs average weights variation compared to the previous year

383

In this study, the weighting method was employed with the primary aim of preventing information overlap among indicators. Consequently, the methodology allocates lower weights to those indicators that show a high correlation coefficient with other indicators and higher weights to those who do not share information with other indicators.

387

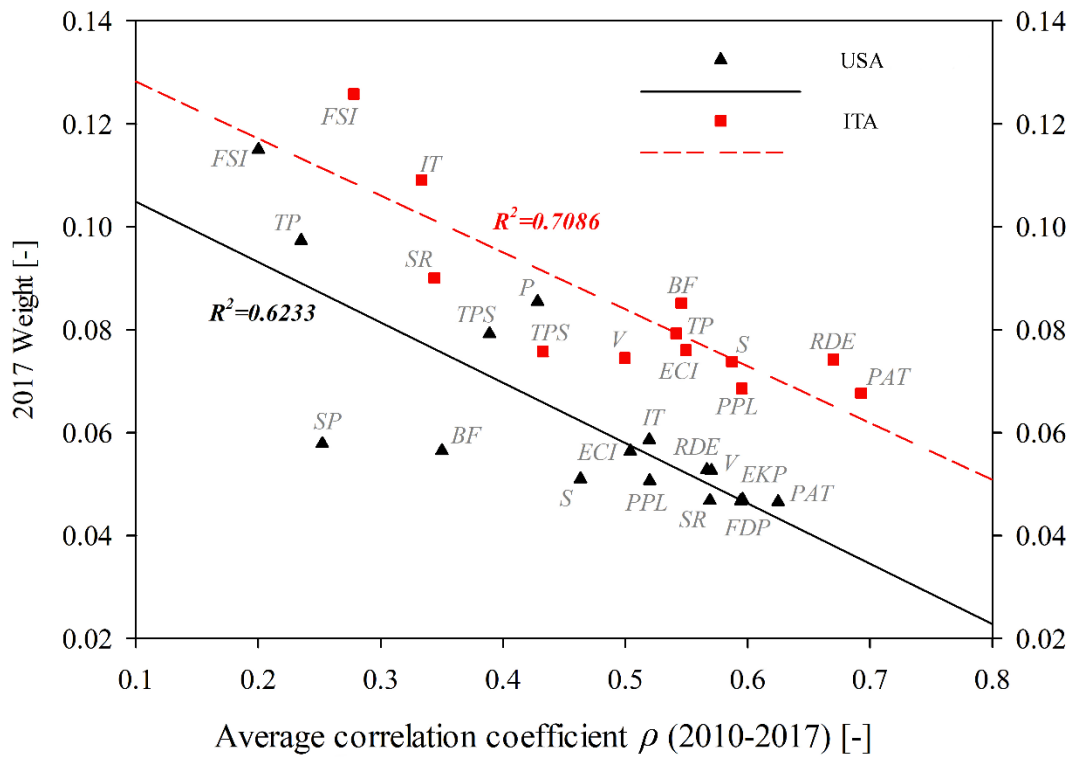
Figure 12 illustrates the relationship between each of the indicator's average correlation coefficient (taken as absolute value) and the weight of each indicator, from 2010 to 2017. The figure shows a good relationship between the average correlation coefficients for all the years and the weights. Thus, a low weight is assigned whenever the indicator shows a high correlation coefficient with the other indicators while a high weight is assigned when the reverse is the case.

392

Based on this postulation, one can assume that the relationship between the correlation coefficients and the weights improves as the number of cases increases. To confirm this assumption, the graph shown in Figure 12 is repeated for all the years. The R^2 of each plot is obtained and then plotted against the years, as shown in

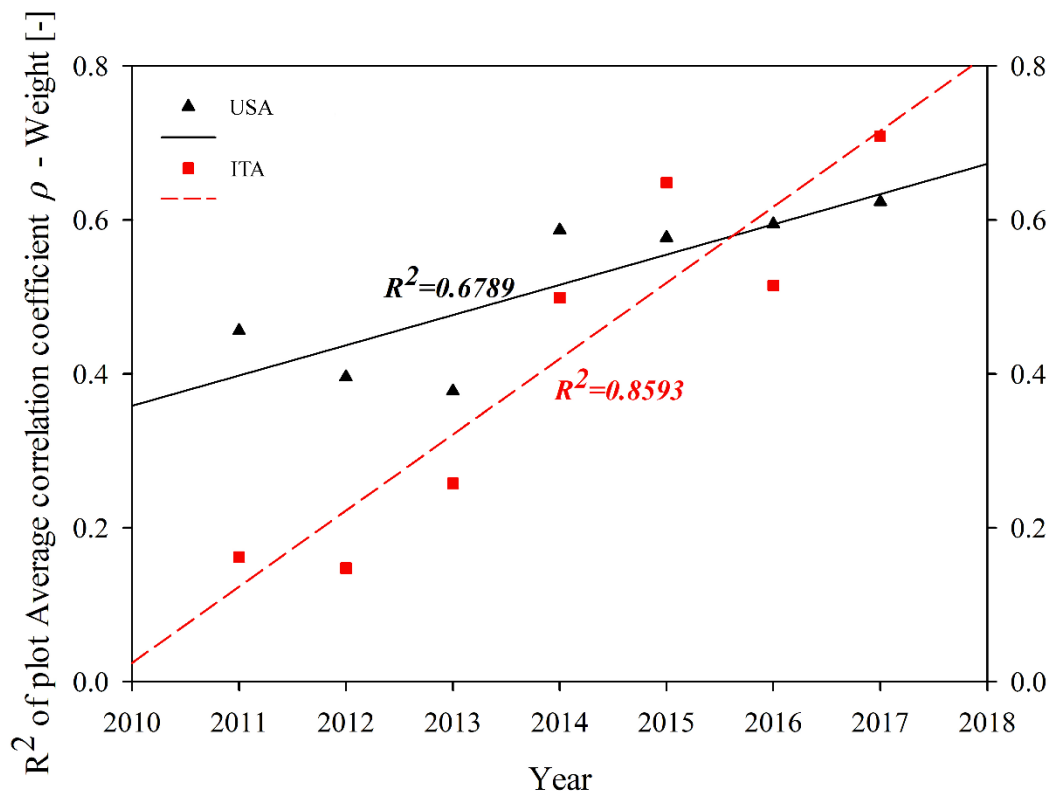
394

395 Figure 13. The results obtained in Figure 13 confirm that the relationship between the correlation coefficients
 396 and the weights improves with time.



397
 398 **Figure 12:** Correlation coefficient of each indicator averaged over the years 2010-2017 vs weight of each
 399 indicator referred to the analysis carried out for the year 2017.

400



401

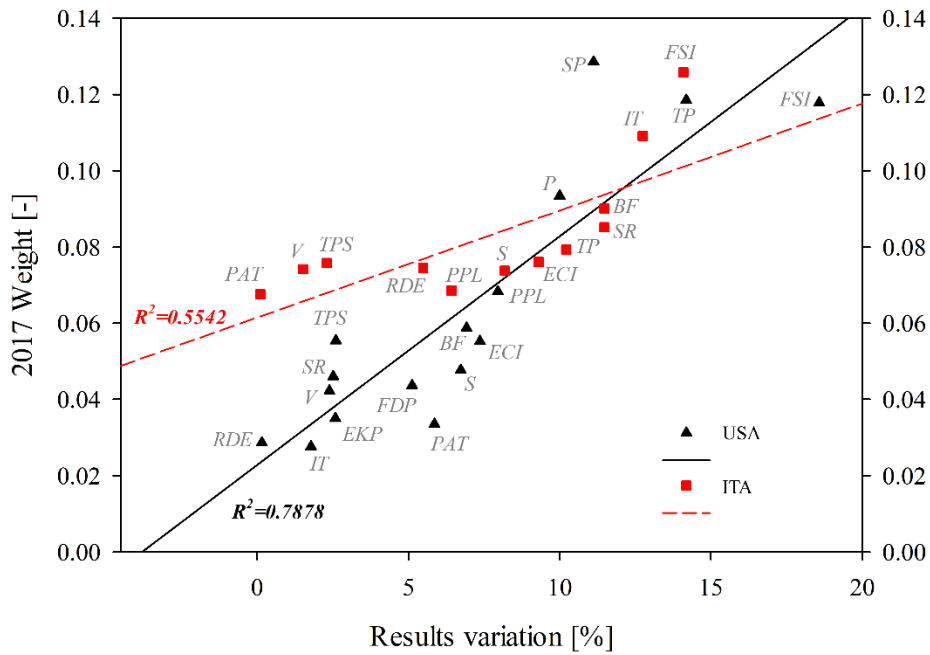
402

Figure 13: Years vs the R^2 of plot in Figure 12 repeated for every year

403

404 4.2.3 Sensitivity analysis

405 It can also be assumed that a good algorithm allocates the highest weights to the indicators whose absence can
 406 alter the results. Such allocation is presumed to be possible, irrespective of the methodology that is being
 407 employed for assigning weights. This assumption can also be confirmed by performing a sensitivity analysis,
 408 which is done by removing one variable at a time, then comparing the consequent RFS with the value obtained
 409 when all indicators are taken into consideration. The results shown in Figure 14 reveal a good relationship
 410 ($R^2 = 0.7878$) between the assigned weight and the variation of results when the indicator is not taken into
 411 consideration. This relationship appears to be stronger in the analysis carried out for the United States than
 412 Italy ($R^2 = 0.5542$). Nevertheless, such disparity is attributable to the lack of events (*i.e.* years).



413

414 **Figure 14:** Sensitivity analysis of indicators showing the variation in the value of RFS if the indicator is
 415 removed from the analysis, plotted against the weight value of the indicator.

416 **5. Conclusions and discussion**

417 This paper proposes a new approach to compute resourcefulness at the community and national scales.
 418 Resourcefulness is deemed one of the main components of disaster resilience. The methodology involves
 419 normalizing, weighting, and aggregating data of selected resourcefulness indicators to obtain a resourcefulness
 420 index. The problem of missing data has been tackled in the paper using the Multiples Imputation and the
 421 Markov Chain Monte Carlo (MCMC) methods.

422 As a case study, the proposed methodology has been applied to two countries, namely the USA and Italy.
 423 Results show that the two main issues in the methodology are the size of the data sample and the type of data
 424 collected. The former can affect the reliability of the analysis in the case of data paucity while the latter can
 425 prevent any comparison between different communities/countries if the data structure is not the same.
 426 Comparability among regions may be achieved by defining fixed and consistent criteria for the data collection
 427 process. Therefore, there is a need for a standard data collection methodology to be implemented by all regions
 428 so the outputs can be compared.

429 The reliability of the Principal Components Analysis can be improved by decreasing the number of indicators
430 (*i.e.* increasing ratio cases/variables). To do so, a more concise set of indicators can be derived out of the
431 existing ones. Further discussion on the selection of indicators is therefore needed to identify which to keep
432 and which to remove. Data availability is also an important issue since the methodology is data-driven. The
433 amount and quality of data are what determines the trustability of results. Data sources can vary according to
434 the case study. The sources used for the case study presented in the paper are not valid for another case study.
435 Ideally, the competent authorities who are interested in applying this methodology to their case, whether it is
436 a community or a country, should have access to the data that can feed the methodology. Therefore, data
437 availability would not be an issue for them.

438 The proposed approach will help decision-makers specialized in the resource and funds allocation sectors to
439 assess their resourcefulness level and, hence, improve their response to natural hazards and manmade disasters.

440 Future work will focus on solving the issue of data availability and collection by proposing a procedure that
441 does not rely entirely on hard data but on also expert judgment, such as the Bayesian Network.

442

Dim.	Indicator	Symb.	Sources for the USA	Sources for Italy
Political-economic	Economic Complexity	<i>ECI</i>	https://atlas.media.mit.edu/en/	https://atlas.media.mit.edu/en/
	Bureaucracy Flexibility	<i>BF</i>	https://www.heritage.org/index/	https://www.heritage.org/index/
	Fragility	<i>FSI</i>	http://fundforpeace.org/fsi/data/	http://fundforpeace.org/fsi/data/
	Mitigation Spending	<i>MS</i>	n/a	n/a
	Safety Rate	<i>SR</i>	https://www.statista.com/statistics/191219/reported-violent-crime-rate-in-the-usa-since-1990/	https://www.statista.com/statistics/91219/reported-violent-crime-rate-in-the-usa-since-1990/
	Participation in public life	<i>PPL</i>	https://www.fairvote.org/voter_turnout#voter_turnout_101	https://www.tgcom24.mediaset.it/politica/infografica/1-andamento-storico-dell-affluenza-alle-urne_1001472-2018.shtml
	Preparedness	Smartphone penetration	<i>S</i>	https://www.statista.com/statistics/201183/forecast-of-smartphone-penetration-in-the-us/
Disaster Preparedness		<i>FDP</i>	https://ncdp.columbia.edu/	n/a
Emergency Kit Preparedness		<i>EKP</i>	https://ncdp.columbia.edu/	n/a
Trust	Safety Perception	<i>SP</i>	https://www.statista.com/statistics/205525/public-perception-of-trend-in-crime-problem-in-the-usa/	https://www.istat.it/it/files//2018/06/EN_Fear_of_crime.pdf
	Volunteering	<i>V</i>	https://www.statista.com/statistics/189295/percentage-of-population-volunteering-in-the-united-states-since-2003/	https://www.lastampa.it/2012/12/04/blogs/datablog/il-volontariato-in-italia-

			basWoxRZc2U9svassRt6TO/pagina.html
	Interpersonal Trust	<i>IT</i>	https://gssdataexplorer.norc.org/variables/441/vshow https://www.statista.com/statistics/641012/level-of-interpersonal-trust-italy/
	Trust in the political system	<i>TPS</i>	http://www.people-press.org/2017/12/14/public-trust-in-government-1958-2017/ http://www.realinstitutoelcano.org/ps/portal/rielcano_en/contenido?WC_M_GLOBAL_CONTEXT=/elcano/elcano_es/zonas_es/europa/ari39-2018-toygur-guide-to-understanding-italy-2018-elections-and-beyond
	Trust in the police	<i>TP</i>	https://news.gallup.com/poll/213869/confidence-police-back-historical-average.aspx https://www.statista.com/statistics/579685/public-trust-in-state-police-italy/
	Patriotism	<i>P</i>	https://news.gallup.com/poll/236420/record-low-extremely-proud-americans.aspx?utm_source=twitter&utm_medium=twitter&utm_campaign=sharing n/a
Creativity	Patent applications	<i>PAT</i>	https://data.worldbank.org/indicator/IP.PAT.NRES?locations=US&view=chart https://www.statista.com/statistics/412674/european-patent-applications-from-italy/
	Research and development expenditure	<i>RDE</i>	https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?display=graph https://www.statista.com/statistics/420976/gross-domestic-expenditure-on-research-and-development-gdp-italy/

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