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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.

1. Introduction

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

Figure 1 presents a conceptual definition of resilience, introduced by Bruneau et al. (2003). In the figure, the functionality (Q) of a system ranges from 0% to 100%, where 100% and 0% imply full availability and unavailability of services, respectively. A system can be defined as a group of components that jointly deliver a service or a group of services. Therefore, a community can be considered as a system of systems as it is composed of physical and social systems (Kammouh et al. 2018c). The occurrence of a disaster at time t_0 causes damage to the system, and this produces an instant drop in the system's functionality (ΔQ) (Kammouh et al. 2018e). Afterward, the system is restored to its initial state over the recovery period ($t_1 - t_0$) with a restoration rate R. Theoretically, resilience is defined as the ability to "prepare, absorb, recover from actual or potential adverse events" (NRC 2015). From the definition, resilience deals not only with already occurring disaster events but also with potential events that may occur in the future. Therefore, resilience quantification cannot be based solely on deterministic studies but should be expressed in a probabilistic manner. For example, as shown in Figure 1, every component of resilience (i.e., ΔQ, t0, t1, R) may have a certain probability distribution (Cimellaro et al. 2010b). The resilience function in the figure is, therefore, the function corresponding to the mean value of every resilience parameter.

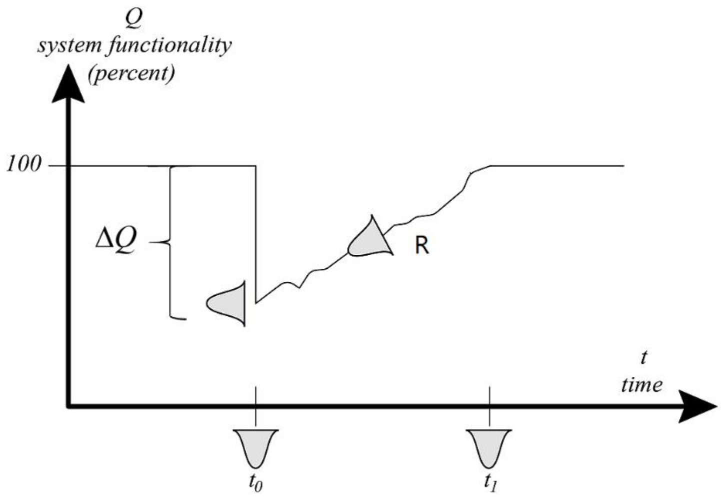

Figure 1: Measuring the seismic resilience considering uncertainties

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

- **Redundancy**: refers to the community's ability to provide alternative options for effective and efficient management of emergency situations;
- **Robustness**: refers to the system's ability to withstand a certain level of stress and consequently preserve its functionality;
- **Rapidity**: refers to the rate at which the community attain at least its pre-event functionality level;
- **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".

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.

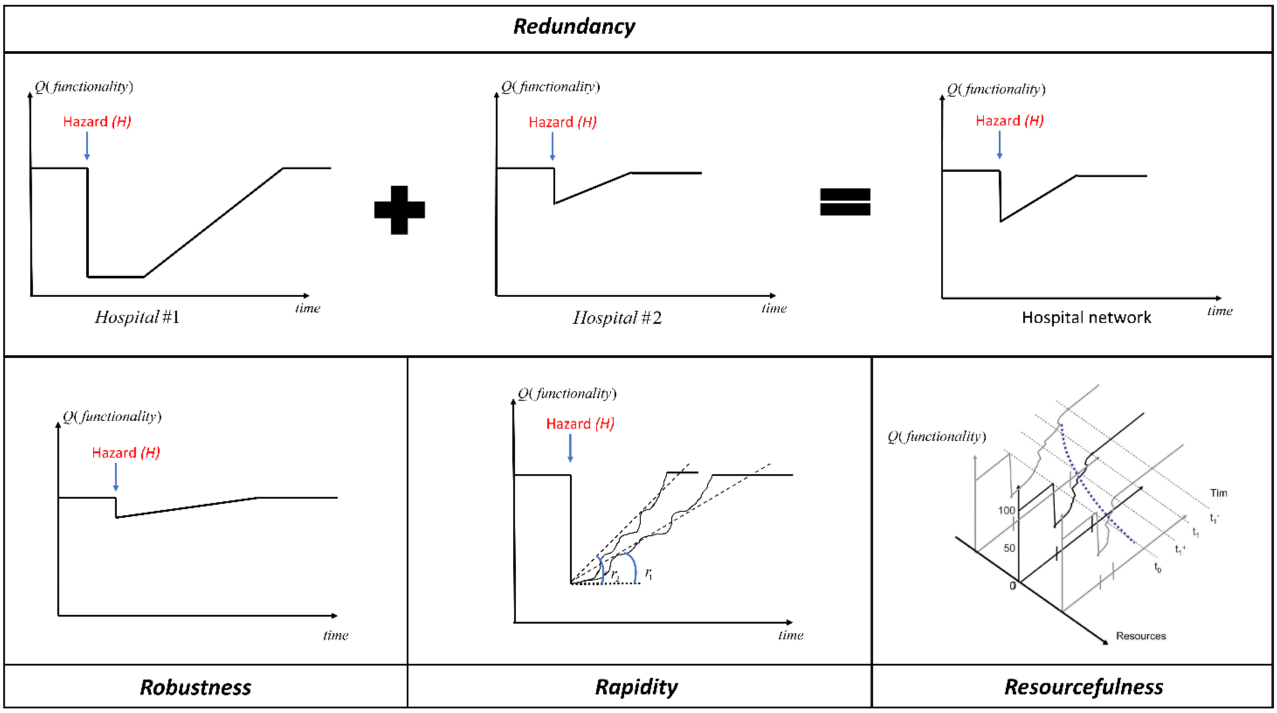

Figure 2: Visual representation of the resilience characteristics

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

2. Resourcefulness definition and principles

2.1. Resourcefulness definition

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

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

Table 1 Resourcefulness definitions

	Resilience dimensions	Definition of Resourcefulness
(Bruneau et al. 2003)	- 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)	- 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.”

2.2. Resourcefulness principles

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

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

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

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

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

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

3. Methodology

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:

- **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.

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

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

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

1. Defining the index principles;

2. Data selection;
3. Imputation of missing data;
4. Normalization;
5. Weight allocation;
6. Aggregation;
7. Uncertainty and sensitivity analysis.

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

3.1. Data selection and imputation

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

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

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

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

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

Missing data imputation is done as follows:

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

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

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

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

3.2. Normalization

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

To ensure a successful normalization of data, a potentially suitable approach is to choose an external value known as *Target Value* (Balbi et al. 2018; Cutter et al. 2010; Kammouh et al. 2018d). This value serves as a normalizing benchmark and is considered an optimum value for the given indicator. Every indicator must have an optimal value *TV* and that value must be properly chosen. The same normalization method has been adopted in the PEOPLES framework (Kammouh and Cimellaro 2018; Kammouh et al. 2019b), which is a hierarchical framework for assessing the resilience of communities at different scales. It comprises seven dimensions, summarized by the acronym PEOPLES, which stands for population, environmental and ecosystem, organized governmental services, physical infrastructures, lifestyle, economic development, and social capital. In their case, however, each normalized indicator cannot be higher than 1. Therefore, 1 is used in place of x/TV whenever the indicator x is higher than *TV*.

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

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

3.3. Weights allocation

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

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

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

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

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

$$\mathrm{cov}(Y_i, Y_j) = 0 \tag{6}$$

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

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

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

$$S = \begin{bmatrix} s_{11} & \cdots & s_{1N} \\ \vdots & \ddots & \vdots \\ s_{N1} & \cdots & s_{NN} \end{bmatrix} \tag{8}$$

where

$$s_{ij} = \mathrm{cov}(x_i, x_j) \tag{9}$$

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

$$\mathrm{P} = \begin{bmatrix} \rho_{11} & \cdots & \rho_{1N} \\ \vdots & \ddots & \vdots \\ \rho_{N1} & \cdots & \rho_{NN} \end{bmatrix} \tag{10}$$

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

$$\rho_{ij} = \mathrm{corr}(x_i, x_j) = \frac{\mathrm{cov}(x_i, x_j)}{\sigma_{x_i}\sigma_{x_j}} \tag{11}$$

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

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

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

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

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

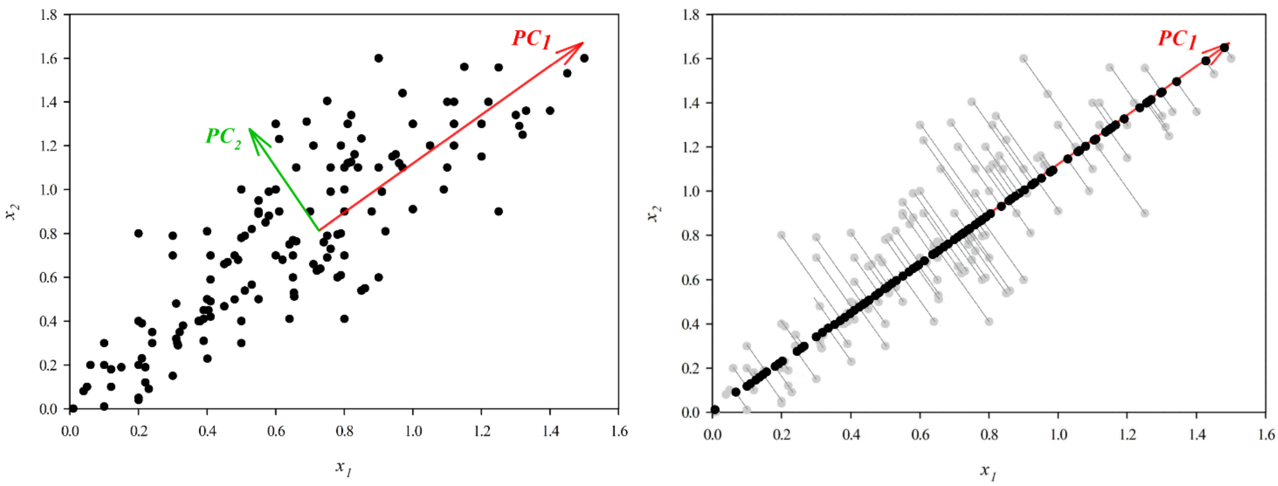

Figure 3: (a) Hypothetical data distribution and principal components, (b) Selection of the first principal component.

3.4. Aggregating indicators

The last step of the methodology is the selection of an aggregation technique. There are two main methods that have been proposed in the literature: Additive aggregation and Geometric aggregation (Commission 2008). The additive aggregation method allows full compensability among indicators, whereas the geometric method partially prevents compensability. For example, Paton and Johnston (2017) investigated the contribution of the *Hakka spirit* to the response of the Taiwanese community in the aftermath of an earthquake that took place in 1999. The term *Hakkas* refers to Han Chinese, who migrated to other countries including Taiwan. The specific approach they usually adopt in response to natural hazards is termed “the spirit of the sturdy neck”. This statement simply means holding on firmly in the face of extreme adversity. The term can also mean “to keep on doing something without any regard to your strength”. According to the authors, this mindset was instrumental to the quick recovery of Tung Shih town after the earthquake. On its part, the government responded quickly, even though its progress was limited by the inadequacy of essential materials and the city’s unpreparedness. Nevertheless, the *Hakka spirit* effectively mitigated the impacts of this lack of preparedness, and this supports the additive aggregation since the absence of some resources did not prevent responding to the disaster. Therefore, Additive aggregation is the most suitable aggregation method for computing the resourcefulness composite index because it allows compensability among indicators. Mathematically, the additive aggregation is represented as follows:

$$RFS_{c,y} = \sum_{i=1}^{Q} x_{yj} \cdot w_j \tag{13}$$

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

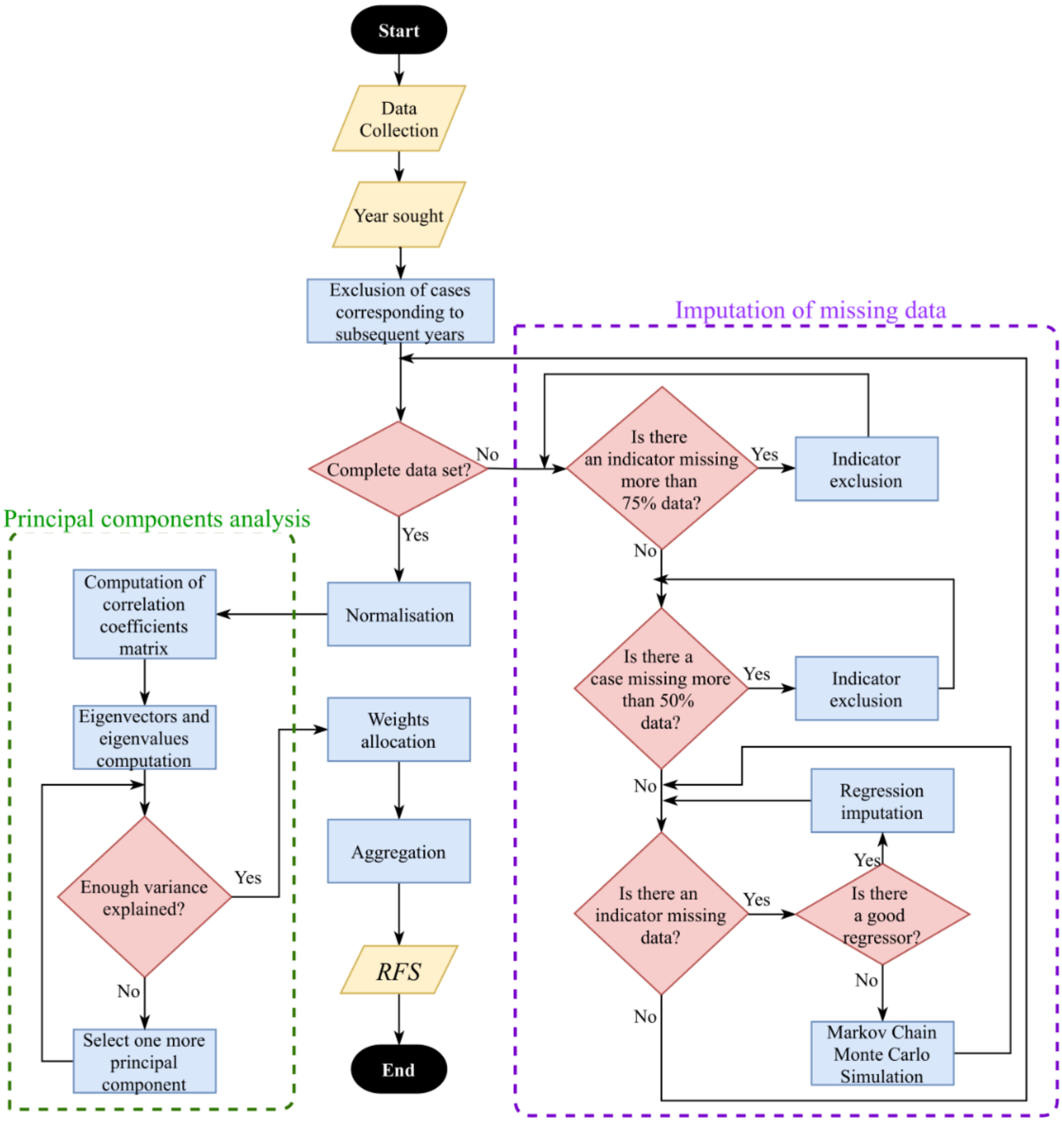

Figure 4: Flow chart of the resourcefulness assessment methodology

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

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

4.1 Imputation of missing data

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

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

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

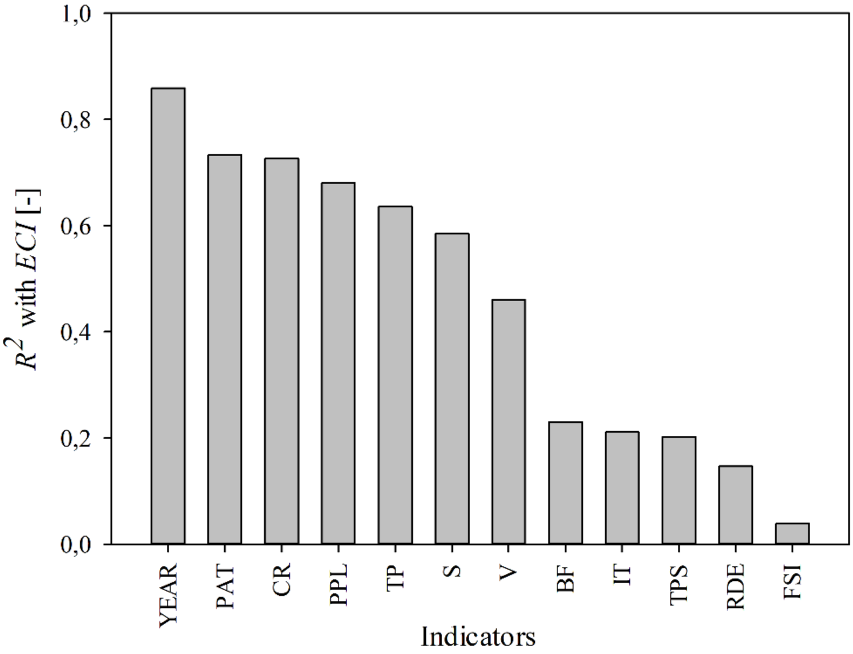

Figure 5: Selection of regressors for the indicator *Economic Complexity ECI for Italy*

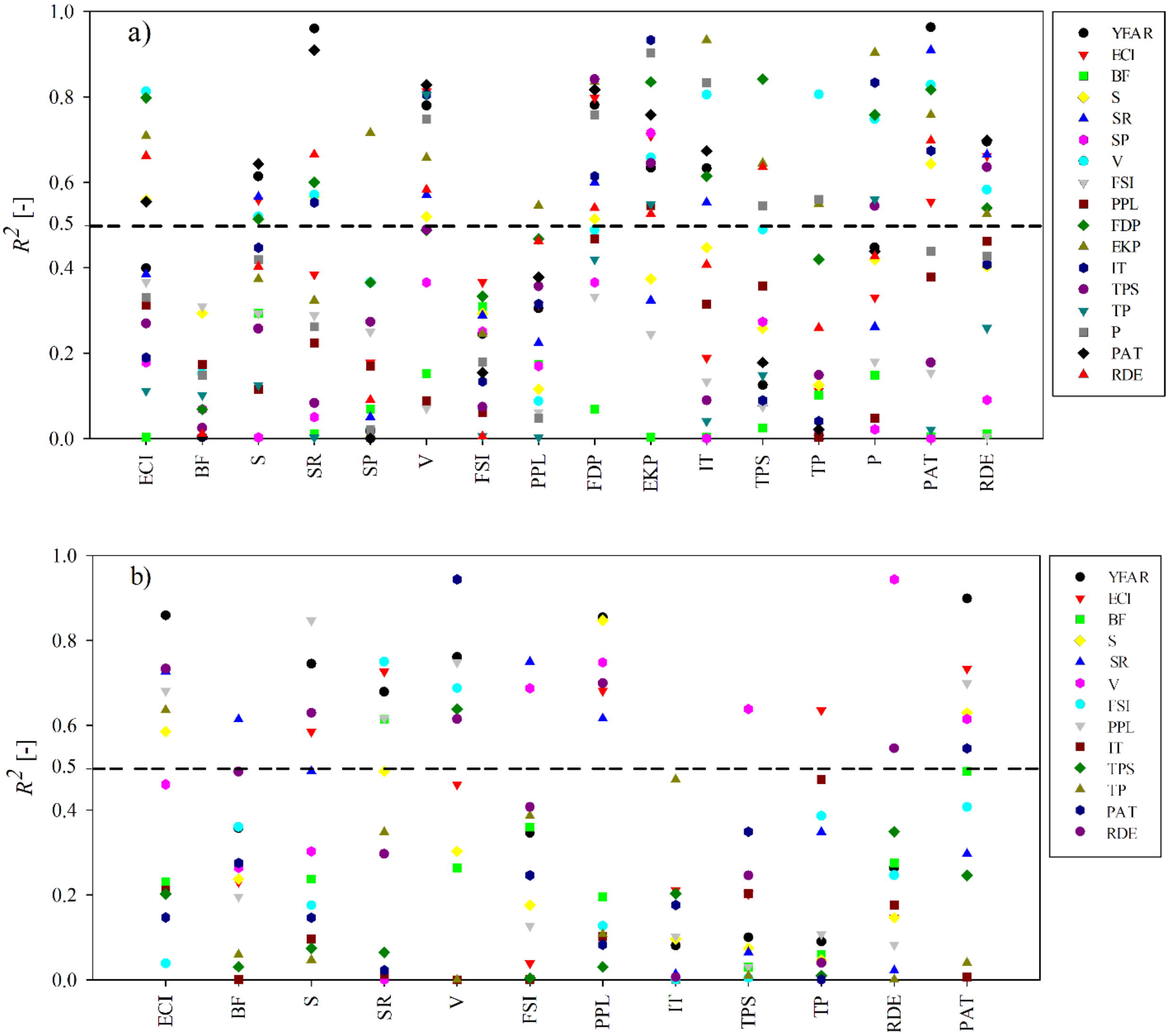

Figure 6: Selection of good regressors for each indicator for (a) the USA and (b) Italy

4.2 Results

4.2.1 Resourcefulness results

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

$$RFS_{USA,2017} = 0.4605 \tag{14}$$

$$RFS_{ITA,2017} = 0.3954 \tag{15}$$

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

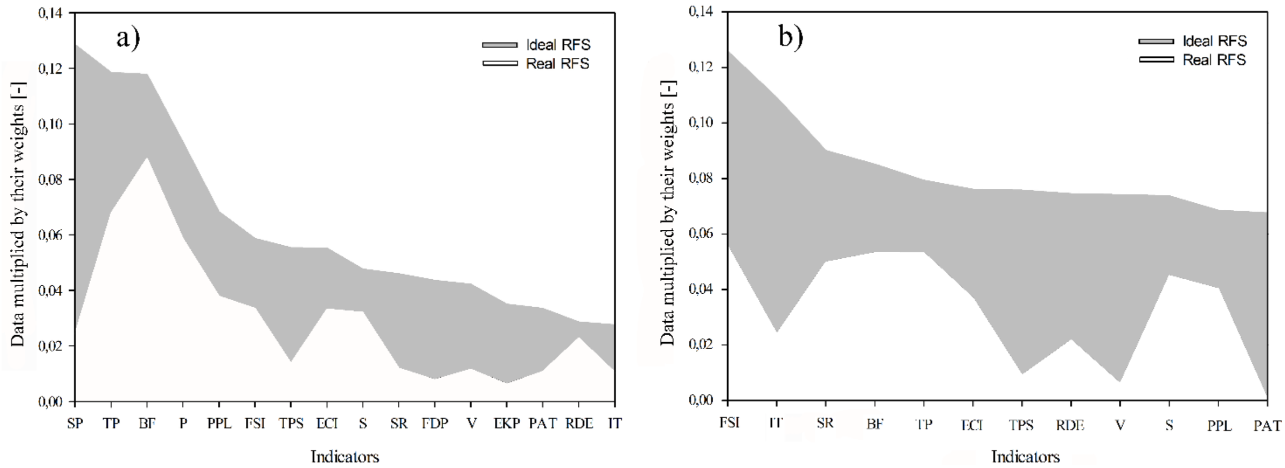

Figure 7: (a) USA's *RFS* and (b) Italy's *RFS*

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

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

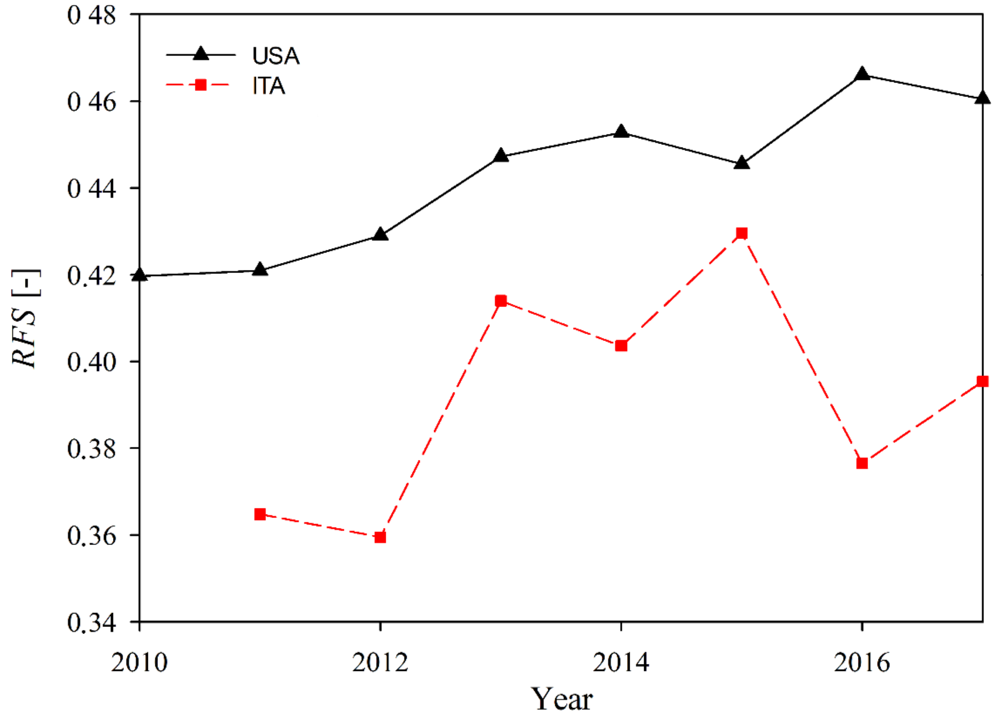

Figure 8: Evolution of *RFS* over the years of the USA and Italy

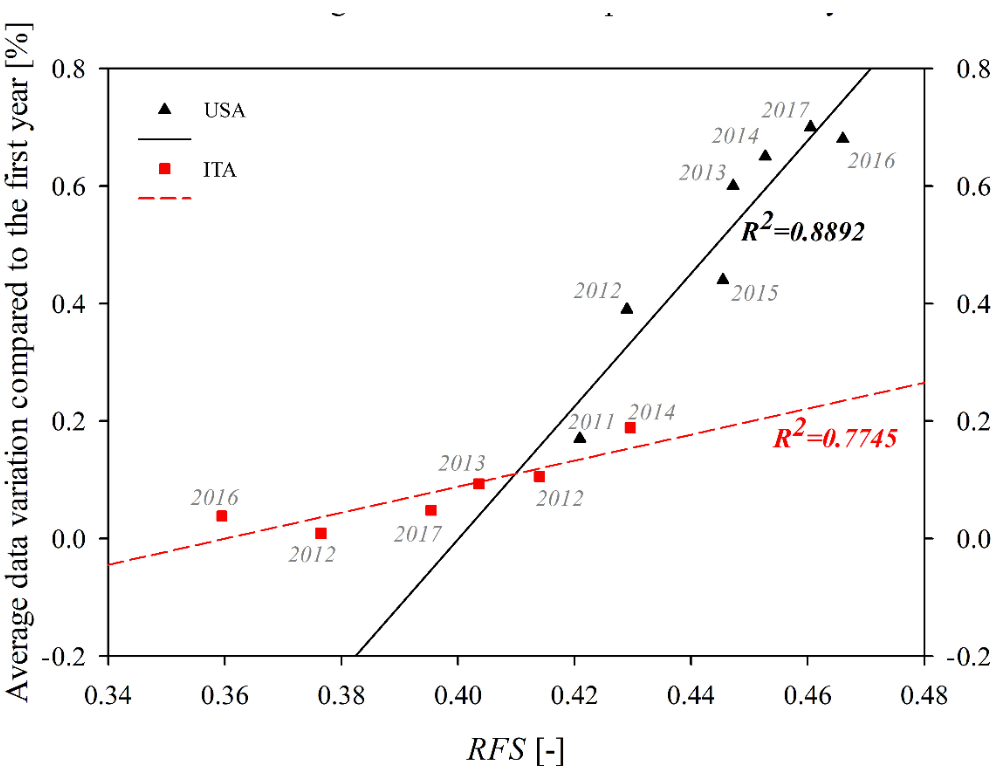

Figure 9: RFS over the years vs percentage average data variation compared to the first year

4.2.2 Weights results

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

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

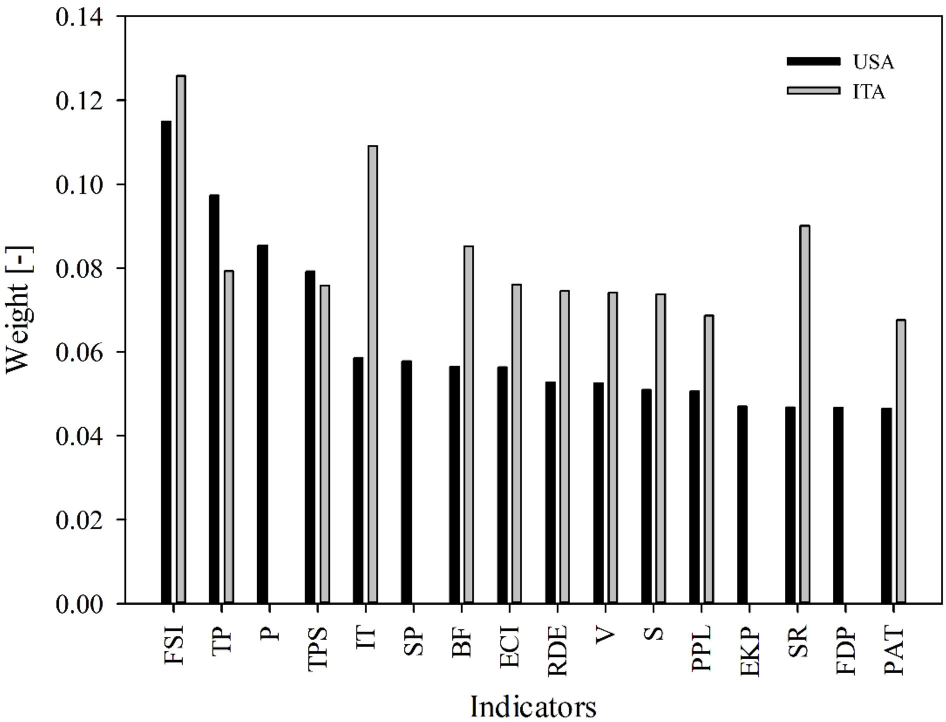

Figure 10: 2017 weights for Italy and the United States

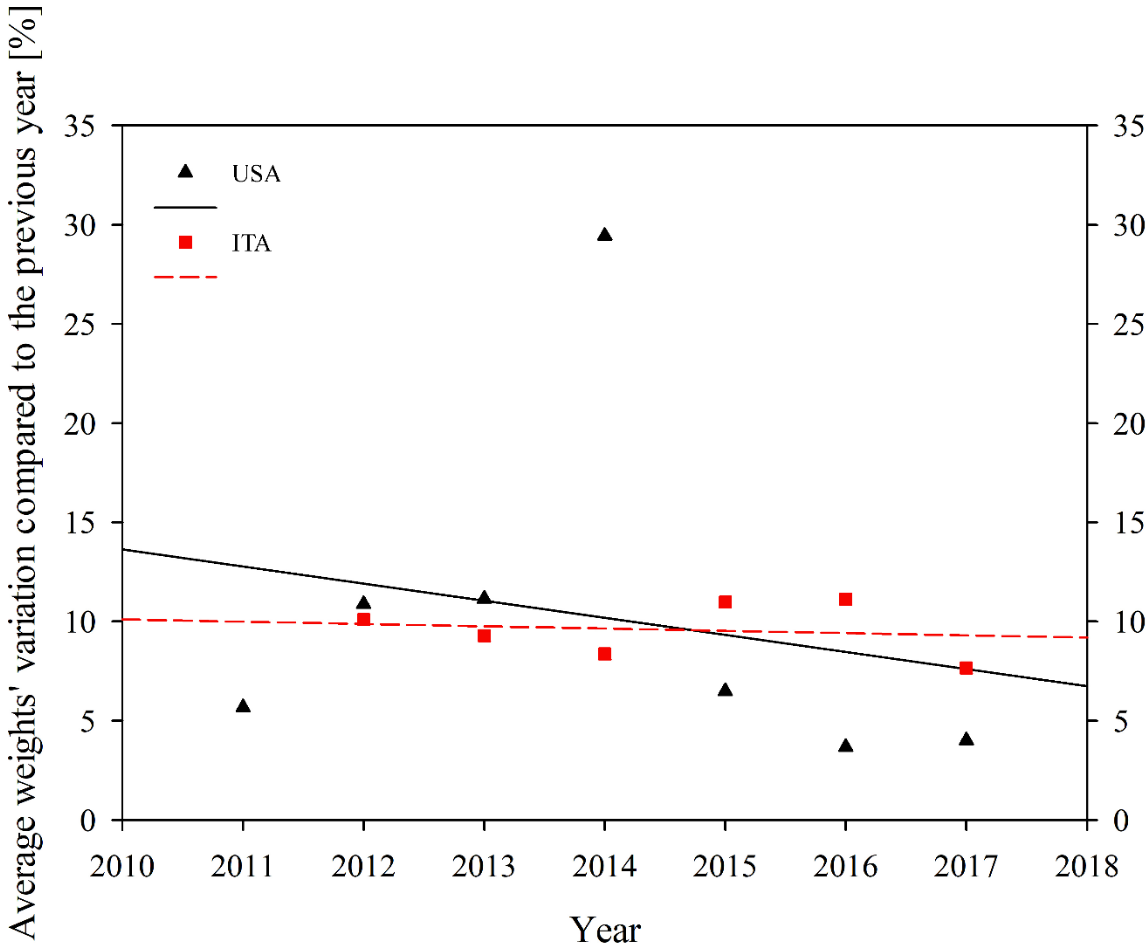

Figure 11: Years *vs* average weights variation compared to the previous year

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.

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.

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

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

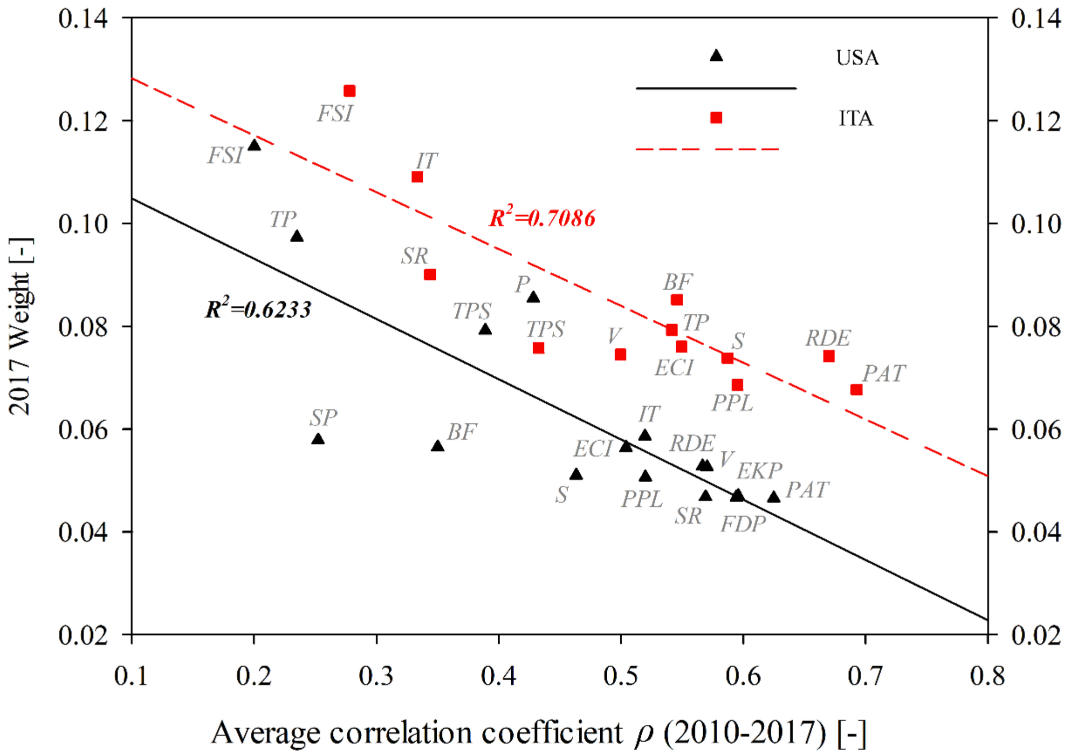

Figure 12: Correlation coefficient of each indicator averaged over the years 2010-2017 *vs* weight of each indicator referred to the analysis carried out for the year 2017.

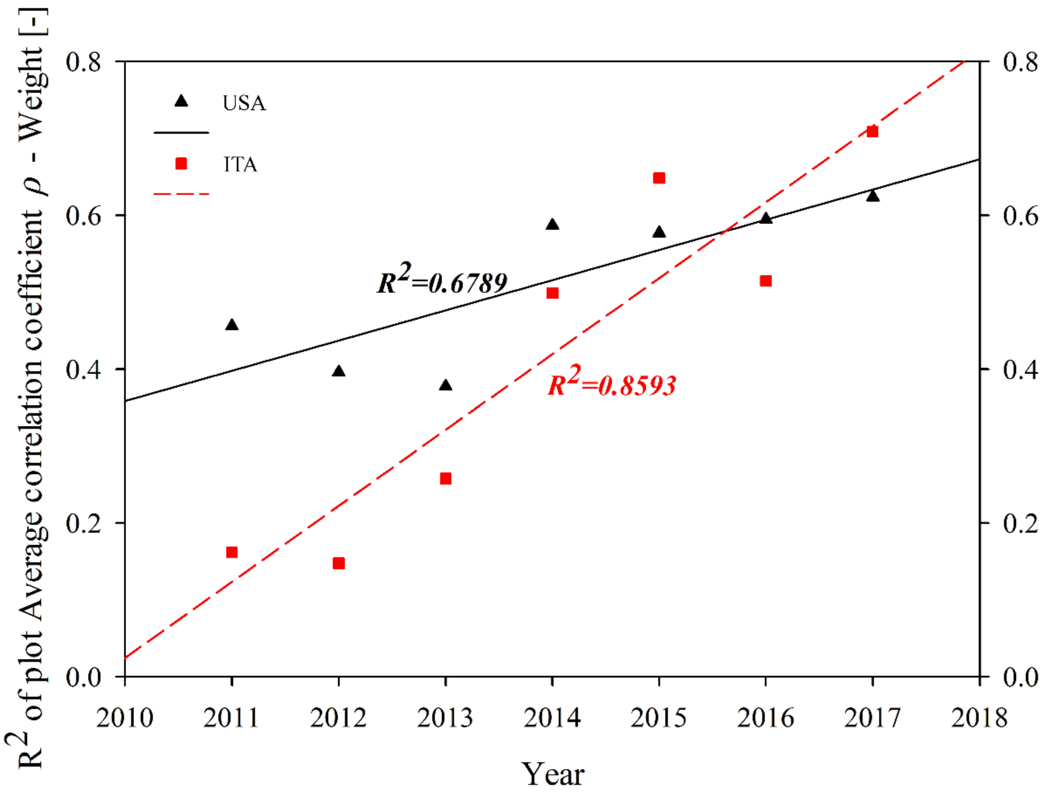

Figure 13: Years *vs* the R^2 of plot in Figure 12 repeated for every year

4.2.3 Sensitivity analysis

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

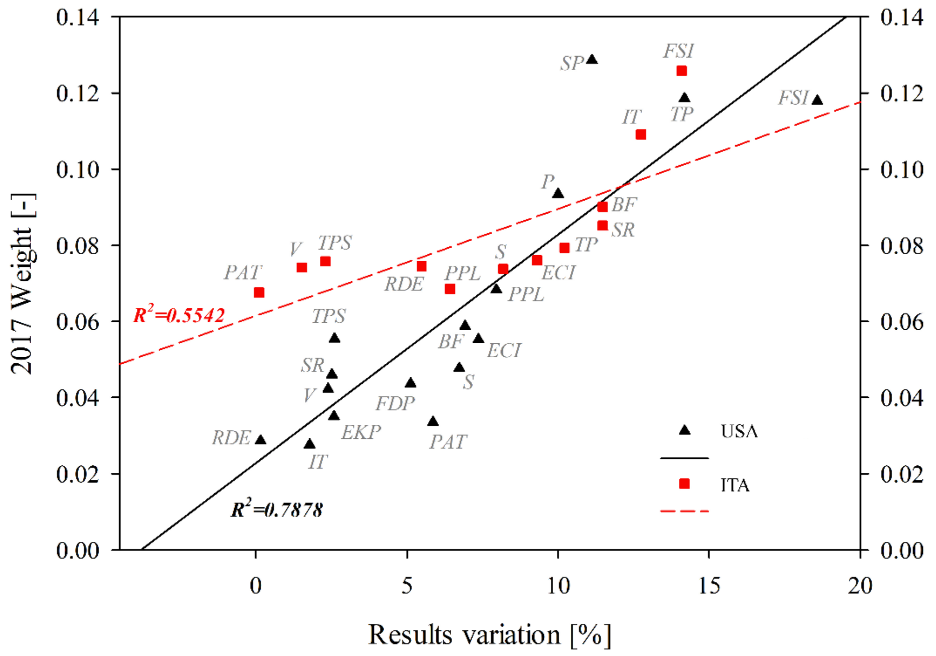

Figure 14: Sensitivity analysis of indicators showing the variation in the value of RFS if the indicator is removed from the analysis, plotted against the weight value of the indicator.

5. Conclusions and discussion

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

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

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

The proposed approach will help decision-makers specialized in the resource and funds allocation sectors to assess their resourcefulness level and, hence, improve their response to natural hazards and manmade disasters. Future work will focus on solving the issue of data availability and collection by proposing a procedure that does not rely entirely on hard data but on also expert judgment, such as the Bayesian Network.

Appendix. Summary of indicators used for the case study of the United States and Italy with data sources

Dim.	Indicator	Symb.	Sources for the USA	Sources for Italy
Political-economic	Economic Complexity	*ECI*	https://atlas.media.mit.edu/en/	https://atlas.media.mit.edu/en/
	Bureaucracy Flexibility	*BF*	https://www.heritage.org/index/	https://www.heritage.org/index/
	Fragility	*FSI*	http://fundforpeace.org/fsi/data/	http://fundforpeace.org/fsi/data/
	Mitigation Spending	*MS*	n/a	n/a
	Safety Rate	*SR*	https://www.statista.com/statistics/191219/reported-violent-crime-rate-in-the-usa-since-1990/	https://www.statista.com/statistics/191219/reported-violent-crime-rate-in-the-usa-since-1990/
	Participation in public life	*PPL*	https://www.fairvote.org/voter_turnout#voter_turnout_101	https://www.tgcom24.mediaset.it/politica/infografica/l-andamento-storico-dell-affluenza-alle-urne_1001472-2018.shtml
Preparedness	Smartphone penetration	*S*	https://www.statista.com/statistics/201183/forecast-of-smartphone-penetration-in-the-us/	https://www.statista.com/statistics/201183/forecast-of-smartphone-penetration-in-the-us/
	Disaster Preparedness	*FDP*	https://ncdp.columbia.edu/	n/a
	Emergency Kit Preparedness	*EKP*	https://ncdp.columbia.edu/	n/a
Trust	Safety Perception	*SP*	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	*V*	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	*IT*	https://gssdataexplorer.norc.org/variables/441/vshow	https://www.statista.com/statistics/641012/level-of-interpersonal-trust-italy/
	Trust in the political system	*TPS*	http://www.people-press.org/2017/12/14/public-trust-in-government-1958-2017/	http://www.realinstitutoelcano.org/wps/portal/rielcano_en/contenido?WCM_GLOBAL_CONTEXT=/elcano/elcano_es/zonas_es/europa/ari39-2018-toygur-guide-to-understanding-italy-2018-elections-and-beyond
	Trust in the police	*TP*	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	*P*	https://news.gallup.com/poll/236420/record-low-extremely-proud-americans.aspx?utm_source=twitterbutton&utm_medium=twitter&utm_campaign=sharing	n/a
Creativity	Patent applications	*PAT*	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	*RDE*	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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