Resilience Assessment of Urban Communities

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Abstract

The multiple uncertainties of both natural and man-made disasters have prompted increased attention in the topic of resilience engineering. In this paper, an indicator-based method for measuring urban community resilience is proposed. The method is based on the PEOPLES framework, which is a hierarchical framework for defining disaster resilience of communities at various scales. It consists of seven dimensions summarized with the acronym PEOPLES: Population; Environment; Organized governmental services; Physical infrastructures; Lifestyle; Economic; and Social capital. Each of the dimensions is split into several components and indicators, which have been derived by the authors or collected from a wide range of literature. Each indicator is represented using a performance function, which portrays the functionality of the indicator in time. Higher functionality of the indicator leads to higher resilience of the community. These functions can be constructed in a systematic manner using damage and restoration parameters. The aggregation of the performance functions, passing through the different hierarchical levels of PEOPLES framework, leads to one function that represents the dynamic performance of the analysed community. This paper also introduces a matrix-based interdependency technique that serves as a weighting scheme for the different indicators. As a

case study, the proposed methodology is applied to the city of San Francisco for which a resilience curve and a resilience metric have been computed.

Keywords: PEOPLES framework; disaster recovery; resilience indicators; interdependency; resilience quantification; urban communities

INTRODUCTION

Community resilience has gained increased attention due to the recent natural and man-made disasters. Resilience itself is a multidisciplinary and broad concept. In engineering, resilience is the ability to "withstand stress, survive, adapt and bounce back from a crisis or disaster and rapidly move on" (Wagner and Breil 2013). The term resilience was defined by Allenby and Fink (2005) as "the ability of a system to remain in a practical state and to degrade gracefully in the face of internal and outside changes". Bruneau et al. (2003) defined resilience as "the ability of social units to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways to minimize social disruption and mitigate the effectors of further earthquakes". The definition given by Bruneau et al. (2003) and extended by Cimellaro et al. (2010) is adopted in this study.

Several solutions for measuring resilience are available in the literature (Cimellaro 2016; Cimellaro et al. 2016a; Cimellaro et al. 2016c; Cimellaro et al. 2014). Chang and Shinozuka (2004) introduced a measurement framework to quantitatively assess the disaster resilience of communities. They proposed a series of resilience measures in a probabilistic context based on the work by Bruneau et al (2003). The proposed framework has been implemented in a case study of the Memphis water system under an earthquake event. However, social and economic aspects were not clearly integrated within the framework. Gilbert and Ayyub (2016) proposed microeconomic models and metrics to quantify the economic resilience of engineering systems. These metrics provide a sound basis for the development of effective decision-making tools for multi-hazard environments and lead to significant savings through risk reduction and expeditious recovery. Liu et al. (2017) introduced a method that combines dynamic modelling with resilience analysis. Interdependent critical infrastructures have been analysed using the framework by performing a numerical analysis of the resilience conditions in terms of design, operation, and control for a given failure scenario. Cimellaro et al. (2016b) proposed a resilience index for water distribution networks which is the product of three parameters. This index has been used to compare different restoration plans in a small town in the South region of Italy. Similarly, an index has been proposed to measure resilience of a gas distribution network (Cimellaro et al., 2013). Ouyang et al. (2012) proposed a multi-stage framework to analyze infrastructure resilience establishing an expected annual resilience metric by defining a series of resilience-based improvement strategies for each stage. Kammouh et al. (2017a) have introduced a quantitative method to assess the resilience at the state level based on the Hyogo Framework for Action (UNISDR 2007). The approach introduced was an evolution of the risk assessment concept. The resilience of 37 countries has been evaluated and a resilience score between 0 and 100 has been assigned to each of them (Kammouh et al. 2017a; Kammouh et al. 2018b; Kammouh and Cimellaro 2018). Ayyub (2015) proposed other resilience metrics with clear relationships to the most relevant definition of the reliability and risk notions. The framework meets logically consistent requirements drawn from the measure theory considering the recovery phase based on spatial and temporal considerations. Kwasinski et al. (2016) proposed a hierarchical framework for assessing resilience at the community level. The model is represented through community dimensions and their relationships with community services, systems, and resources. Several challenges that can influence a comprehensive community resilience assessment methodology have been identified. However, natural resources, as an important element in the resilience planning process, have not been considered in the proposed framework.

By looking at the available measurement tools, it is possible to distinguish some features that separate them. Some are top-down measurement schemes, others are bottom-up, some measurements schemes are purely qualitative in their approach, and others are quantitative. PEOPLES framework is an example of a top-down approach that starts with the big picture (i.e. resilience) and then breaks down into smaller segments. Each subsystem is then refined in yet greater detail, sometimes in many additional subsystem levels, until the entire specification is reduced to base elements (Cimellaro et al. 2016a). The acronym PEOPLES combines seven dimensions of a community: Population; Environment; Organized government services; Physical infrastructure; Lifestyle; Economic; and Social capital. It is classified as a quantitative framework for designing and measuring the resilience of communities (Kammouh et al. 2017b; Kammouh et al. 2018c). Another top-down measurement tool is the Baseline Resilience Indicator for communities (BRIC) (Cutter et al. 2014). This tool is also quantitative but it focuses more on the inherent resilience of communities. BRIC is practically oriented towards the fieldwork unlike the PEOPLES framework whose application is still within the research field. San Francisco Planning and Urban Research Association framework (SPUR) (SPUR 2009) is a qualitative framework that measures the capability to recover from earthquakes. The framework considers the restoration of buildings, infrastructures, and services to assess the resilience of the physical infrastructure. Examples of other top-down approaches are: the Hyogo Framework for Action (HFA) (UNISDR 2005); the UK Department for International Development (DFID)

Interagency Group (Twigg 2009b); ResilUS (Miles and Chang 2011); etc. There also exist bottom-up approaches which are mainly designed to help communities predict and plan for resilience. These bottom-up measurement tools take an all-hazards approach in their assessment. They are generally qualitative types of assessments that the community does itself, or it works with local stakeholders to derive its assessment. Some bottom-up approaches include: the Conjoint Community Resiliency Assessment Measure (CCRAM) (Cohen et al. 2013); the Communities Advancing Resilience Toolkit (CART) (Pfefferbaum et al. 2011); the Community Resilient System (White et al. 2015); etc. A more exhaustive list of resilience measurement tools classified according to several characteristics can be found in (Cutter 2016).

Several other works have been carried out to define and quantify the resilience of communities but mostly with a focus on engineering systems (Woods 2017; Park et al. 2013; Hosseini et al. 2016; Jovanović et al. 2016; etc.). Measuring resilience is among the most difficult tasks due to the intricacy involved in the process. Although the use of indicators is perceived as an important instrument to measure the resilience of a system, developing a standardized set of resilience indicators is clearly challenging for such a dynamic, constantly reshaping and context-dependent concept. Cutter et al. (2014) assert that research on quantifying community resilience is still at the preliminary stage. Even though much efforts has already been made to boost research on community resilience indicator (Cutter et al. 2010; Norris et al. 2008; Twigg 2009a), there is still no acceptable method for the evaluation of community resilience and there are still challenges in developing real evaluation strategies (Abeling et al. 2014).

This study aims at presenting an exhaustive quantitative method for calculating the resilience of urban communities within the context of the PEOPLES framework (Cimellaro et al. 2016a). The objective of this work is to use the structure of PEOPLES framework to derive a tool to quantify the resilience of urban communities. The method starts by collecting all community resilience indicators found in the literature. The collected indicators are first filtered to ensure a minimum overlapping between them, then they are allocated to the PEOPLES' components. A single measure is assigned to each indicator allowing it to be quantifiable. Each measure is represented using a performance function, which represents the functionality of the indicator in time. Higher functionality of the indicator leads to higher resilience of the community. These functions can be constructed in a systematic manner using damage and restoration parameters. All measures are weighted according to their contribution in the resilience assessment using a new matrix-based interdependency technique. The performance functions of the indicators are aggregated, passing through the different level of PEOPLES framework, into one function that represents the dynamic performance of the whole community. The resilience of the community is finally computed as the area under the final performance function for a defined control time following the disaster.

RESILIENCE EVALUATION

According to Bruneau et al. (2003), the resilience of a system depends on its functionality performance. The functionality of a system is the ability to use it at possibly an impaired level. This term is also referred to as functionality, which is a broad definition describing how easily a system can be serviced or repaired. For example, a system with modular, hot-swappable components would have a good level of functionality. The conceptual approach described in Bruneau et al. (2003) is illustrated in Fig. 1. The functionality performance (Q) ranges from 0 %

to 100 %, where 100% and 0% imply full availability and non-availability of services, respectively. 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). Afterward, the system is restored to its initial state over the recovery period (t_1-t_0). The loss of resilience is considered equivalent to the quality degradation of the system over the recovery period. Mathematically, it is defined by Eq. (1):

$$LOR = \int_{t_0}^{t_1} \left[100 - Q(t)\right] dt \tag{1}$$

where LOR is the loss-in-resilience measure, t_0 is the time at which a disastrous event occurs, t_1 is the time at which the system recovers to 100% of its initial functionality, $Q(t)$ is the functionality of the system at a given time t.

The approach introduced above considers a constant initial functionality (Q_0=100%). This can be problematic if the system recovery includes mitigation and hardening actions that increase the functionality to a level beyond the initial state of the system. Therefore, in this paper, the initial functionality is signified by a functionality (Q_0) that can take any value between 0% and 100% (Fig. 2). This means that the functionality function does not necessarily start with 100%, which leaves room for possible improvements in case mitigation and hardening actions are included in the recovery process. Moreover, the LOR has to be normalized to be time-independent by dividing over T_c, which is the control time of the period of interest (Cimellaro et al. 2010). Thus, Eq. (1) can be replaced by Eq. (2):

$$LOR = \int_{t_0}^{t_1} \frac{\left[100 - Q(t)\right]}{T_c} dt \tag{2}$$

PEOPLES FRAMEWORK

PEOPLES framework is an expansion of the research on resilience, and its attributes were developed at the Multidisciplinary Centre of Earthquake Engineering Research (MCEER) (Cimellaro et al. 2016a). The framework provides a procedure to measure the community resilience at different scales (spatial and temporal) by evaluating the infrastructures performance considering their interdependency. The method proposed in this study adopts the structure of the PEOPLES framework for its implementation. PEOPLES framework comprises seven dimensions of community summarized with the acronyms PEOPLES. The seven dimensions are:

1. Population and demographics: identifies the focal community population. The aim of this dimension is to understand the ability and expertise of the society in managing adverse impacts and to recover quickly from disasters;
2. Ecosystem and environmental: signifies the capability of the ecological system to overcome a disturbance and return to its pre-event state;
3. Organized governmental services: specifies the community sectors readiness to respond to an event, and plays a key role in raising community resilience both before (preparedness and mitigation strategies) and after (response and restoration) a disaster;
4. Physical infrastructure: addresses lifelines and facilities that have to be restored to a functional state after the disaster;
5. Lifestyle and community competence: represents both the raw abilities of a community (e.g., skills to find multifaceted solutions to complex problems through the engagement in political networks) and the perceptions of a community (e.g., perception to have the ability to do a positive change through a common effort that relies on PEOPLES' aptitude to resourcefully envision a new future and then move in that direction);
6. Economic development: consists of both the current economy (static state) of a community and its future growth (dynamic development). It represents the capability of

the society to keep up in the aftermath of a disaster by means of good substitution, employments, and services redistribution.

7. Social-cultural capital: describes the extent to which the people are willing to stay within their area and help their community to bounce back after the disaster.

Further details on each of the above dimensions can be found in (Cimellaro et al. 2016a).

THE METHODOLOGY: RESILIENCE QUANTIFICATION OF COMMUNITIES BASED ON THE PEOPLES FRAMEWORK

The method introduced in this section can take any indicator-based framework as a conceptual basis. For this study, the PEOPLES framework is considered due to its wide recognition within the disaster resilience community. The structure and organisation of PEOPLES framework allows preventing possible overlap among the indicators. Once the framework is fixed, relevant indicators are selected to describe the framework's components in detail. Every indicator found in the literature has been collected and then they are filtered with 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. The interdependency between the variables is tackled by introducing an interdependency matrix technique. The proposed interdependency technique returns as an output a weighting factor for each variable. Once the contribution of the different variables toward the overall resilience is determined, the variables are measured using past data. In the proposed resilience assessment method, the variables are represented by a continuous functionality function rather than a crisp number. Finally, the functionality functions of the different variables are aggregated to obtain a single community functionality function that is used to evaluate the resilience of the community. In the following, the methodology is described in all details.

PEOPLES' dimensions, components, indicators, and measures

PEOPLES is a framework for quantifying and defining disaster resilience of a community at various scales. It is divided into seven dimensions, each of which is further divided into several components. The goal is to convert PEOPLES from its current qualitative version to a quantitative framework. To do so, all resilience indicators found in the literature have been collected and then allocated to the proper components of PEOPLES. Much effort has been done to reduce the overlapping among indicators by removing duplicated ones. This has led to a condensed list of 115 indicators (see Appendix A). Each indicator has a measure assigned to it to make all indicators computable. Each measure is normalized with respect to a fixed quantity, the target value (*TV*). The target value is an essential quantity that provides the baseline to measure the resilience of a system (Cutter et al. 2010). The system's existing functionality at any instance of time is compared with the target value to know how much functionality deficiency is experienced by the system. For instance, if we consider the measure "Red cross volunteers per 10,000 people" (indicator 7.6.1 in Appendix A), the output of this measure would be an absolute number of volunteers that cannot be incorporated with other measures unless it is normalized; therefore, the result is divided over *TV*, which in this scenario represents the 'optimum' amount of volunteers per 10,000 people (e.g. *TV*=100 volunteers /10,000 people). If the *ratio* between the value of the measure and the *TV* is less than one, it implies that the indicator could still be enhanced. If the *ratio* is bigger than one, a value of 1 is assigned to that measure. Having all measures normalized empowers the comparison among systems of similar or different natures (e.g. hospitals and water networks).

The measures are classified under two different categories: 'Static measure (*S*)', which describes the measures that are not affected by the disastrous event, and 'dynamic measure (*D*)' or 'event-sensitive measure', which describes the measures whose values change after the occurrence of the disaster. In addition, each of the PEOPLES' variables (dimensions, components, indicators) contributes with a certain degree towards the resilience output. Therefore, they are classified according to their importance. A weighting factor for each variable is computed using an interdependency matrix technique which considers the interdependency among the PEOPLES' variables. A variable is said to be important if other variables depend on it to deliver their function. A comprehensive list of PEOPLES elements including dimensions, components, and indicators, with their corresponding natures (*S* or *D*) is tabulated in Appendix A. For some indicators in which high values correspond to low levels of resilience, a rescaling process involves reversing the order of their contribution to the overall resilience index is presented.

Weighting factors: the interdependency matrix technique

Indicators do not contribute equally to the overall resilience output. In this paper, weighting factors are allocated to the different variables of PEOPLES based on an interdependency analysis. For the purpose of the analysis, the variables of PEOPLES are classified into three major groups as follows:

1. Indicators that fall within a component are considered as a group;
2. Components classified under a dimension are taken as a group;
3. PEOPLES seven dimensions make a group.

The proposed interdependency technique assumes that the variable's importance is strictly related to the number of other variables in the same group that depend on it. Variables in the same groups are put together in a $[\boldsymbol{n}\times\boldsymbol{n}]$ square matrix (Fig. 3), where n is the number of variables in the analysed group. The cells in the matrix can take the values 0 or 1. The value 0 means that the functionality of the variable in the row does not depend on the variable in the column, while the value 1 means that the variable in the row depends on the variable in the column. The importance factor of each variable is obtained by summing up the numbers in each column of the matrix. A high value implies high importance of the corresponding variable. The interdependency analysis is done in a hierarchical manner (Fig. 4). That is, an interdependency matrix is built for each group of variables so that each variable is analysed within the group it belongs to. For instance, a single interdependency matrix is constructed for the seven dimensions of PEOPLES. An interdependency matrix is built to each group of components under the dimensions. Finally, every group of indicators under the components are analysed independently by performing the above introduced interdependency technique. This results in 37 matrices to perform a full interdependency analysis for the different variables of the framework. The number of matrices depends on the conceptual framework used. That is, frameworks that use less variables and simpler structure would require a smaller number of interdependency matrices.

The matrix can be filled using a walk down survey. The evaluation is performed through an expert and the information is readily provided in a (yes/no) or (1/0) form. Like in any walk down survey, the assessment is denominated by subjectivity and so the evaluation process is prone to vagueness type uncertainty. However, due to the comprehensive structure of PEOPLES framework, the responsible expert will not have difficulties filling the survey and will not have to do arbitrary guessing. The experts will be able to employ their knowledge to decide whether the answer should be yes or no (1 or 0). To reduce possible vagueness and uncertainty, the survey can be filled by a group of experts. That is, the interdependency between any two variables is determined by more than one person. Then, a statistical analysis is performed considering a normal distribution, which is suitable for such statistical problems. Therefore, each variable is represented by a normal probability distributed function (PDF) (Fig. 5). Three values from each PDF can be used in the consequent analysis: the mean value (σ), the mean value + the standard deviation ($\sigma + \mu$), and the mean value – the standard deviation ($\sigma - \mu$). This results in a final resilience output with the uncertainty bound being considered.

The interdependency between the variables is greatly related to the community type. Fig. 6 shows the level of interdependency between the seven dimensions of the PEOPLES framework for three different kinds of communities: urban, rural, and industrial. The area enclosed by the interdependency polygon for the urban community is greater than the others. This indicates a high level of interaction and interdependency for urban communities. Also, the development level of the community plays a role in identifying the interdependency among resilience components because developed communities require more interdependent systems to increase service efficiency. Other factors such as the type of hazard can also affect the interdependency matrix.

Another aspect that is rarely discussed is the temporal alteration of the interdependency. After a perturbation, systems find a new equilibrium, which implies that the relationships between the system's elements change. Therefore, the interdependency matrix does not remain the same after a disaster event takes place (Fig. 7). Although this is true for every system, in this study the temporal effect is not considered as it would add up unnecessary complexities which do not reflect the priorities of decision makers.

The importance factors of the variables in the same group can be normalized using a Min-Max rescaling technique to create a set of comparable variables. The Min-Max rescaling technique is a method in which each variable is scaled between zero and one (a score of 0 being the worst rank for a specific variable and a score of 1 being the best) (Cutter et al. 2010). This scaling procedure subtracts the minimum importance factor from the importance factor of the underlying variable and divides it over the range of the importance factors, as shown in Eq. (3).

$$w_{v_i} = \frac{\sum_{j=1}^{n} a_{ji} - \min\left[\sum_{j=1}^{n} a_{ji}\ for\, i = 1,\dots,n\right]}{\max\left[\sum_{j=1}^{n} a_{ji}\ for\, i = 1,\dots,n\right] - \min\left[\sum_{j=1}^{n} a_{ji}\ for\, i = 1,\dots,n\right]} \tag{3}$$

where w_{vi} is the weighting factor of the i^{th} variable (v_i), a_{ji} is the interdependency value between variable j and variable i (Fig. 3), n is the total number of variables in the analysed group.

The above technique assumes that at least one variable is assigned a weighting factor equal to 0. This implies that the variable with a 'zero' weighting factor does not contribute to the overall resilience. In this research, a simpler technique that divides the importance factor over the maximum importance factor, as indicated in Eq. (4), is used.

$$w_{v_i} = \frac{\sum_{j=1}^{n} a_{ji}}{\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ji}} \tag{4}$$

Eq. (4) transforms the importance factor of each variable into a weighting factor *(w*). The equation is applicable to each group apart. Weighting factors are then multiplied by their corresponding functionality functions (q), as indicated in Eq. (5):

$$q_i^* = w_i \times q_i \tag{5}$$

where q_i* is the weighted functionality function of variable i, q_i is the functionality function of variable i in analyzed group.

Derivation of the final functionality function and computing resilience

Each variable is represented by a functionality function; uniform function for event-non-sensitive measures 'static measures' and non-uniform function for event-sensitive measures 'dynamic measures' (see Fig. 8). The functionality function can be defined using a set of parameters that mark the outline of the functionality function (e.g. initial functionality q_0, post disaster functionality q_1, restoration time T_r, recovered functionality q_f, etc.). These parameters can be obtained from the past events and/or by performing hazard analyses specific to each measure. Afterwards, all functionality functions are weighted based on their contribution in the resilience assessment, as described in the previous section. The summation of the weighted functionality functions of the variables in the same group is considered to move to an upper layer. That is, to obtain the functionality function of component *j*, the summation of the weighted functionality functions of the indicators under component *j* is considered. Similarly, to obtain the functionality function of dimension *i,* the sum of the weighted functionality functions of the components under dimension *i* is considered. Finally, the functionality function of the community is the summation of the weighted functionality functions of the seven dimensions.

The conceptual approach for the consolidation of functionality functions through the different hierarchical levels of the framework is depicted in a flowchart (see Fig. 9). The final functionality function represents the functionality of the community over time. It is obtained using the Eq. (6):

$$R(t) = \sum_{i=1}^{d=7} w_i(t).D_i(t) \tag{6}$$

where $R(t)$ is the resilience function of the community, $w_i(t)$ is the weighting function of dimension *i*, $D_i(t)$ is the functionality function of dimension *i*. In this equation, the weighting factors are written as a function of t because generally the weight of variable cane change after the perturbation. The functionality function of dimension i is obtained using Eq. (7):

$$D_i(t) = \sum_{j=1}^{n_i} \left(w_{i,j}(t).C_{i,j}(t) \right) \tag{7}$$

where $w_{i,j}(t)$ is the weighting function of the component j under dimension i, $C_{i,j}(t)$ is the functionality function of component j under dimension i, n_i is the number of components under dimension i. This function is obtained by aggregation the functionality functions of the indicators in the same group. Eq. (8) can be used to do the operation:

$$C_{i,j}(t) = \sum_{k=1}^{n_{i,j}} \left(w_{i,j,k}(t).I_{i,j,k}(t) \right) \tag{8}$$

where $w_{i,j,k}(t)$ is the weighting function of the indicator k under component j, which belongs to dimension i, $I_{i,j,k}(t)$ is the functionality function of indicator k under component j, which belongs to dimension i, $n_{i,j}$ is number of indicators under component j, which belongs to dimension i. The resilience of the community R can then be evaluated as the area under the functionality function $R(t)$ for a defined time following the disaster event, known as the 'control period' t_c. Eq. (9) expresses the resilience index in its most explicit form using only the known parameters:

$$R = \int_{t=t_0}^{t_c} R(t).dt = \int_{t=t_0}^{t_c} \left\{ \sum_{i=1}^{d=7} w_i(t). \left[\sum_{j=1}^{n_i} w_{i,j}(t). \sum_{k=1}^{n_{i,j}} \left(w_{i,j,k}(t).I_{i,j,k}(t) \right) \right] \right\}.dt \tag{9}$$

The introduced method is a decision making tool, and the usefulness of the final resilience metric is to give an indication whether the community needs to improve in terms of resilience by comparing it to a given acceptable level. Using this metric, the user can identify immediately if the community is experiencing a high functionality deficiency, then the user can decide to look into specific components and indicators that are found to cause the highest impact on resilience. The significance of the proposed methodology lies in its graphical representation that helps communities take proper actions to improve their resilience. While all previous works generally provide a single index to measure community resilience, the proposed method indicates in details whether the resilience deficiency is caused by the system's lack of robustness or by the slow restoration process. For example, it is possible for two communities to have the same resilience deficiency induced by different reasons (e.g. lack of robustness, slow recovery, etc). This is represented in Fig. 10 where two systems have the same loss of resilience (*LOR*) caused by different reasons. The proposed method recognizes where exactly the resources should be spent to efficiently improve resilience. The final resilience index allows the user to have a broad picture about the resilience of the community, while the functionality curves of single indicators are used for analyses that focus more on specific resilience issues of the community.

CASE STUDY: 1989 LOMA PRIETA EARTHQUAKE, SAN FRANCISCO

In this section, the resilience of the city of San Francisco is evaluated using the proposed resilience method. The case study intends to show the applicability of the proposed methodology and not the actual evaluation of the resilience of San Francisco. The 1989 Loma Prieta earthquake, with a moment magnitude of 6.9 M_w, has been considered as the disaster event. For the purpose of this study, only one of the PEOPLES dimensions 'Physical Infrastructure' has been considered. Table 1 shows the extended list of the components and indicators within the dimension 'Physical Infrastructure'. Each indicator is linked to a measure that describes the indicator numerically. As shown in Fig. 8, dynamic measures (*D*) are interpreted graphically using functionality curves which are determined using a set of parameters (normalized initial functionality q_0, post disaster functionality q_1, restoration time T_r, and recovered functionality q_f), whereas the static measures (*S*) are non-sensitive to the event and remain constant even after the disaster occurrence. In this study, the parameters were determined using open database sources (see notes under Table 1), which offer data on all cities across the US.

In Table 1, q_{0u} is the not-normalized initial functionality of the measure. The normalization of this quantity is necessary to combine it with the other measures that fall in a same group. This is done by defining the parameter TV (target value). This parameter represents the quantity at which the analysed measure is considered fully resilient, and it can be defined by an expert or a group of experts. Therefore, by dividing the non-normalized functionality q_{0u} over the target value TV, one could obtain a normalized functionality q_0 which now can be combined with other indicators in the same group.

Right after the disaster, the functionality function of a dynamic measure drops to q_1 (see Fig. 8b). Recovery actions are started immediately after the event, trying to bring the service back to an acceptable level. In this example, the recovered functionality q_r is assumed equal to the initial functionality q_0. The restoration time T_r is usually determined using probabilistic or statistical approaches. In this case study, restoration fragility curves recently developed by Kammouh et al. (2018a) have been used to determine the restoration time for the different variables (Kammouh and Cimellaro 2017; Kammouh et al. 2018a; De Iuliis et al. 2018). In their work, they have introduced an empirical probabilistic model to estimate the downtime of lifelines following an earthquake. Different restoration functions were derived for different earthquake magnitudes using a large earthquake database that contains data on the downtime of infrastructures. The functions were presented in terms of probability of recovery versus time. The downtime corresponding to 95% of exceedance probability of recovery has been used as a deterministic downtime for the considered infrastructure. As for the rate of restoration, a linear interpolation is assumed for all measures.

Table 2 lists all the parameters required for the realization of the functionality functions. The weighting factors of the different variables under the analysed dimension have been determined using the proposed interdependency matrix technique. Table 3 shows the interdependency matrix of the indicators under the component 'Lifelines'. The report by the National Institute of Standards (NIST 2015) and Technology and the Lifelines Council (CCSF Lifelines Council 2014) have been used to fill the interdependency matrix. The recommendations of some experts in the field were also critical in concluding the matrix. In the matrix, the number '1' represents a significant interdependency while '0' means limited interaction and interdependency between the indicators. The results of the matrix have been used to find the weighting factor of each indicator (see the last row of Table 3). The weighting factors of the different indicators are used in the combination of the different variables to represent the contribution of each of them in the overall resilience evaluation.

Fig. 11 shows graphically the functionality function of two indicators. The first indicator '4.1.1 sturdy housing types' is an event-sensitive indicator (dynamic) for which the functionality level drops after the occurrence of the earthquake (i.e. the functionality decreased from 100 to 59.9 after the disaster). The service is fully restored after 120 days. The second indicator '4.2.3 Physician access', whose measure is "Number of physicians per population", is an event-non-sensitive measure (static) because even if the number of physicians is decreased after the disaster, the ratio of the number of physicians to the total population remains constant. This implies that the functionality level of the measure retains its original level regardless the occurrence of the disaster. The functionality curves of all measures whether they are static or dynamic can be obtained using the data in Table 1. Several data sources were used to compile the data for the case study, such as Census Data (U.S. Census Bureau 2011).

Data collection was a challenging part of the analysis since data about the functionality of community systems is not usually shared with the public. However, this does not imply that data is not available but rather is not accessible. Interested parties, such as decision makers and authorities, can use the framework with its full potential since data is usually available to them.

As explained in the previous section, the functionality functions of the measures under a certain component are combined point by point into a single functionality function, taking into account their weighting factors which have been obtained using the interdependency matrix technique explained before. The weighting factors of the analysed components are presented in Table 1. The functionality function of each component (i.e. facilities and lifeline) was obtained by summing the derived functionality functions of all measures that belong to the underlying component. Similarly, the functionality function of the dimension 'physical infrastructure' was derived by summing the weighted functionality functions of the corresponding components (i.e. facilities and lifelines).

Fig. 12 shows the un-weighted functionality functions of the components facilities and lifelines, and the combined functionality function of the dimension physical infrastructure. The two components have different weighting factors ($I_{Lifelines}$=1, $I_{Facilities}$=0.5). Thus, the combined curve is closer to the high importance component (i.e. Lifelines).

The loss of resilience of the physical infrastructure was computed using Eq. (2). The time interval for calculation of resilience was considered from the time that event occurs (t_0=0) until the end of full recovery (i.e. the time corresponding to the instance where the curve reaches its pre-disaster level; t_r=700 days). The control time T_c can take any value and it is determined based on the period of interest. In this example, T_c is set equal to two years (730 days). The loss of resilience *LOR* in this case study is computed using Eq. (10):

$$LOR_{phys.\inf.} = \int_{t_0}^{t_1} \frac{\left[100 - Q(t)\right]}{T_c} dt = \int_{0}^{700} \frac{\left[100 - Q(t)\right]}{730} dt = 24.7 \tag{10}$$

The area above the functionality curve of the 'physical infrastructure' for the time interval (0 to 700 days) is evaluated and normalized with respect to T_c=730 days. The *LOR* metric is not a percentage but an absolute value that reflects the overall response of the community to the earthquake event. That is, higher *LOR* signifies a poor response of the community. This number significantly depends on the control period. If the control period approaches to infinity, *LOR* tends to be zero. When the control period is short (e.g. 1 or 2 days), the *LOR* tends to be large.

In this case study, the obtained value of *LOR* corresponds only to the physical infrastructure dimension of the community. In order to have a resilience index for the whole community, the functionality functions of other dimensions have to be similarly evaluated and to be combined in the same way the measures were aggregated. It is also interesting to compare the resilience of the two components facilities and lifelines. From Fig. 12, the city of San Francisco has more problems in facilities (*LOR*=30.1) than lifelines (*LOR*=21.2). In this case, it is suggested that the authorities should focus more on enhancing the facilities as the benefit they would get is higher.

CONCLUDING REMARKS

A new indicator-based methodology for evaluating the earthquake resilience of urban communities is presented in this paper. The approach uses the structure of PEOPLES for its implementation. The indicators are defined by weighted functionality functions. The functionality functions are aggregated into a single functionality function, which describes the functionality of the whole community. The methodology has been partially applied to the city of San Francisco by considering one of the seven dimensions of PEOPLES. The indicators in the proposed methodology are modelled in a dynamic fashion. That is, the numeric value of the indicator changes with time, which allows reflecting the recovery rapidity of the indicator. Also, the interdependency among the variables at the same and different levels is considered through the proposed interdependency matrix technique.

The proposed methodology moves beyond the recoverability of the analysed system to also incorporate hardness and adaptive capacity. For example, the hardness capacity is intrinsically reflected in the input parameter q_0 (initial functionality), which can reach a value that is greater than the initial value. In addition, because of its inherent layer-based structure, the methodology permits performing diagnostic and sensitivity analysis to determine the critical indicators. This can be rather important in the design problems.

The proposed resilience assessment approach is adaptable to communities of different types and sizes. It may require some alteration in the adopted measures but the general scheme is the same. Nevertheless, in its current version, it cannot consider uncertainties associated with each indicator as it requires deterministic input data. Future work will specifically focus on this issue through the use of probabilistic and fuzzy-based approaches.

ACKNOWLEDGMENT

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

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Fig. 1. Measuring the seismic resilience

Fig. 2. Evaluating resilience considering the actual initial functionality

Fig. 3. Interdependency matrix between variables in the same group

Fig. 4. Interdependency matrices at the different levels

Fig. 5. Statistical analysis for the expert responses about the weighting factor of each variable

Fig. 6. The variation in the interdependency between the PEOPLES seven dimensions given different types of communities

Fig. 7. Temporal variation in the interdependency matrix

Fig. 8. a) Event-non-sensitive measure (static) b) event-sensitive measure (dynamic)

Fig. 9. Deriving the functionality function of the community

Fig. 10. The resilience curves of two systems showing the loss of resilience LOR

Fig. 11. Example of functionality curves (a) sturdier housing type (dynamic indicator), and (b) Physician access (static indicator)

Fig. 12. Functionality curves of the components, Facilities and Lifelines, under the dimension Physical infrastructure

Table 1. Functionality parameters of the indicators within the Physical Infrastructure dimension for the city of San Francisco after the Loma Prieta earthquake

Component /Indicator	Measure	*w*	*Nat*	q_{0u}	*TV*	q_0	q_1	q_r	T_r (day)
4.1 Facilities	-		-						
4.1.1 Sturdy (robust) housing types	% housing units that are not manufactured homes	0.5	D	1	1	1	0.599	0.998	120
4.1.2 Temporary housing availability	% vacant units that are for rent	0.5	D	2.68	5	0.536	0.050	0.536	620
4.1.3 Housing stock construction quality	100-% housing units built prior to 1970	0.75	D	0.241	1	0.241	0.145	0.241	700
4.1.4 Community services	%Area of community services (recreational facilities, parks, historic sites, libraries, museums) total area ÷ TV	1	D	0.16	0.2	0.800	0.480	0.800	430
4.1.5 Economic infrastructure exposure	% commercial establishments outside of high hazard zones ÷ total commercial establishment	0.75	S	0.85	1	0.850	-	-	-
4.1.6 Distribution commercial facilities	%Commercial infrastructure area per area ÷ TV	0.5	D	0.13	0.15	0.867	0.520	0.867	160
4.1.7 Hotels and accommodations	Number of hotels per total area ÷ TV	0.75	D	102	128	0.797	0.478	0.797	130
4.1.8 Schools	Schools area (primary and secondary education) per population ÷ TV	0.5	D	134	140	0.957	0.574	0.957	90
4.2 Lifelines									
4.2.1 Telecommunication	Average number of Internet, television, radio, telephone, and	0.73	D	5	6	0.833	0.500	0.833	90

	telecommunications broadcasters per household ÷ TV								
4.2.2 Mental health support	number of beds per 100 000 population ÷ TV	0.09	D	69	75	0.920	0.644	0.920	35
4.2.3 Physician access	Number of physicians per population ÷ TV	0.18	S	2.5	3	0.833	-	-	-
4.2.4 Medical care capacity	Number of available hospital beds per 100000 population ÷ TV	0.27	D	544	600	0.907	0.635	0.907	35
4.2.5 Evacuation routes	Major road egress points per building ÷ TV	0.36	S	0.67	1	0.670	-	-	-
4.2.6 Industrial re-supply potential	Rail miles per total area ÷ TV	0.27	D	5412	6000	0.902	0.631	0.902	45
4.2.7 High-speed internet infrastructure	% population with access to broadband internet service	0.18	D	0.9	1	0.900	0.450	0.900	300
4.2.8 Efficient energy use	Ratio of Megawatt power production to demand	1.0	D	0.8	1	0.800	0.160	0.800	25
4.2.9 Efficient Water Use	Ratio of water available to water demand	0.64	D	1	1	1.000	0.240	1.000	60
4.2.10 Gas	Ratio of gas production to gas demand	0.45	D	0.1	1	0.100	0.050	0.100	70
4.2.11 Access and evacuation	Principal arterial miles per total area ÷ TV	0.73	D	172138	200000	0.861	0.602	0.861	45
4.2.12 Transportation	Number of rail miles per area ÷ TV	0.82	D	5412	6000	0.902	0.631	0.902	72
4.2.13 Waste water treatment	Number of WWT units per population ÷ TV	0.55	D	3	4	0.750	0.300	0.750	65

Note: q_{0u} = the initial functionality; TV = the target value; q_0 = the initial normalized functionality; q_1 = post disaster functionality; q_r= the recovered functionality; T_r = the restoration time (Data from US Census Bureau (2011)).

Table 2. The parameters involved in the resilience evaluation

Parameter	Definitoin
Weighting factor (*w*)	The weighting factor of a variable using the proposed

	interdependency matrix technique
Indicator nature (*Nat*):	the indicators are classified according to their nature: "Static (*S*)", assigned to the measures that are not affected by the disastrous event, and "Dynamic (*D*)" or event-sensitive measures, assigned to the measures whose values change after a hazard takes place
Un-normalized functionality before the event (q_{0u})	the un-normalized initial functionality of the measure
Target value (T*V*)	represents the optimal quantity or the baseline for the indicator in order to be considered as fully resilient
Normalized functionality before the event (q_0)	the normalized initial functionality of the measure. It is obtained by dividing the un-normalized functionality q_{0u} over the target value *TV*;
Functionality after the event (q_1)	The normalized residual functionality after the disaster.
Functionality after recovery (q_r)	it is the recovered functionality, which can be equal, higher, or lower than the initial tv (q_0).
Restoration time (T_r)	it is the time needed to finish the recovery process. This value is usually determined using probabilistic or statistical approaches.

Table 3. The interdependency matrix between the indicators under the component 'Lifelines'

Indicator	Telecom.	Mental health support	Physician access	Medical care capacity	Evacuation routes	Industrial re-supply potential	Internet infra.	Efficient energy use	Water Use	Gas	Access and evacuation	Transport.	Waste water treatment
Telecom.	1	0	0	0	0	0	1	1	0	0	1	1	0
Mental health support	0	1	0	1	0	0	0	0	0	0	0	0	0
Physician access	0	0	1	1	0	0	0	0	0	0	0	0	0
Medical care capacity	1	0	1	1	0	0	0	1	1	1	0	1	1
Evacuation routes	0	0	0	0	1	1	0	1	1	1	0	1	1
Industrial re-supply potential	0	0	0	0	1	1	0	1	0	0	1	1	0
internet infra.	1	0	0	0	0	0	1	1	0	0	0	0	0
Efficient energy use	0	0	0	0	0	0	0	1	1	0	1	0	0
Water Use	1	0	0	0	0	0	0	1	1	0	1	1	1
Gas	1	0	0	0	0	0	0	1	1	1	1	1	1
Access and evacuation	1	0	0	0	1	0	0	1	1	1	1	1	1
Transport.	1	0	0	0	1	1	0	1	0	1	1	1	0
Waste water treatment	1	0	0	0	0	0	0	1	1	0	1	1	1
Importance factor	**8**	**1**	**2**	**3**	**4**	**3**	**2**	**11**	**7**	**5**	**8**	**9**	**6**
Weighting Factor	**0.12**	**0.01**	**0.03**	**0.04**	**0.06**	**0.04**	**0.03**	**0.16**	**0.10**	**0.07**	**0.12**	**0.13**	**0.09**

Note: For the level of interdependency if each indicator on the other read across each row
'0' :Limited interaction and dependency on this indicator
'1':Significant interaction and dependency on this indicator

APPENDIX I: DIMENSIONS AND COMPONENTS OF PEOPLES FRAMEWORK

Dimension/ component/indicator	Measure (0 ≤value ≤1)	Ref.	Nat.

1- Population and demographics			
1-1- Distribution\ Density			
-Population density	1-(Average number of people per area ÷ TV)		D
-Population distribution	% population living in urban area		D
1-2- Composition			
-Age	% population whose age is between 18 and 65		S
-Place attachment-not recent immigrants	1-(% population not foreign-born persons who came within previous five years)	Sherrieb et al. (2010)	S
-Population stability	1-% population change over previous five year period	Sherrieb et al. (2010)	S
-Equity	% nonminority population – % minority population		S
-Race/Ethnicity	1-Absolute value of (% white – % nonwhite)		S
-Family stability	% two parent families	Sherrieb et al. (2010)	S
-Gender	1-Absolute value of (%female–%male)		S
1-3- Socio- Economic Status			
-Educational attainment equality	% population with college education – % population with less than high school education		S
-Homeownership	% owned-occupied housing units	Cutter et al. (2014)	D
-Race/ethnicity income equality	1-Gini coefficient	Sherrieb et al.(2010)	S
-Gender income equality	1-Absolute value of (% male median income – % female median income)		S
-Income	Capita household income ÷ TV	Tobin (1999)	D
-Poverty	1-% population whose income is below minimum wage		D
-Occupation	Employment rate %		D
2- Environmental and ecosystem			
2-1- Water			
-Water quality/quantity	Number of river miles whose water is usable ÷ TV		D
2-2- Air			
-Air pollution	1-(Air quality index (AQI) ÷ TV)		D
2-3- Soil			
-Natural flood buffers	% land in wetlands ÷ TV	Beatley and Newman (2013)	S
-Pervious surfaces	Average percent perviousness	Brody et al.	S

-Soil quality	% land area that does not contain erodible soils	(2012) Bradley and Grainger (2004)	S
2-4- Biodiversity			
-Living species	1-% species susceptible to extinction		S
2-5- Biomass (Vegetation)			
-Total mass of organisms	Harvest index (HI) the ratio between root weight and total biomass		S
-Density of green vegetation across an area	Normalized difference vegetation index (NDVI)	Cimellaro et al. (2016a)	D
2-6- Sustainability			
-Undeveloped forest	% land area that is undeveloped forest ÷ TV	Cutter et al. (2008a)	S
-Wetland variation	% land area with no wetland decline	Cutter et al. (2008a)	S
-Land use stability	% land area with no land-use change ÷ TV	UNDE (2007)	S
-Protected land	% land area under protected status ÷ TV	Rubinoff and Courtney (2008)	S
-Arable cultivated land	% land area that is arable cultivated land ÷ TV	UNDE (2007)	S
3- Organized governmental services			
3-1-Executive/ Administrative			
-Health insurance	% population under age 65 with health insurance	Chandra et al.(2011)	S
-Disaster aid experience	Presidential disaster declarations divided by number of loss-causing hazard events ÷ TV	Tierney and Bruneau (2007)	S
-Local disaster training	% population in communities with Citizen Corps program	Godschalk (2003)	S
-Emergency response services	% workforce employed in emergency services (fire-fighting, law enforcement, protection) ÷ TV	Cutter et al. (2008b)	S
-Schools	Number of schools per 1000 students ÷ TV		S
3-2- Judicial			
-Jurisdictional coordination	Governments and special districts per 10,000 persons ÷ TV	Murphy (2007)	S
3-3- Legal/ Security			
-Performance regimes-state capital	Proximity of county seat to state capital ÷ TV	Bowman and Parsons (2009)	S
-Performance regimes-nearest metro area	Proximity of county seat to nearest county seat within a Metropolitan Statistical Area ÷ TV	Bowman and Parsons (2009)	S

3-4- Mitigation/ Preparedness			
-Mitigation spending	Ten year average per capita spending for mitigation projects ÷ TV	Rose (2007)	S
-Nuclear plant accident planning	1-% population within 10 miles of nuclear power plant	Cutter et al. (2014)	S
-Effective mitigation plans	% population covered by a recent hazard mitigation plan	Cutter et al. (2010)	S
-Exposure to hazards	% building infrastructure not in high hazard zones		S
-Protective resources	% land area that consists of windbreaks and environmental plantings	Cutter et al. (2008a)	S
-Financed activities for risk reduction	% governmental financial resources to carry out risk reduction activities ÷ TV	UNISDR (2012)	S
-Essential infrastructure robustness	% of local schools, hospitals and health facilities that remained operational during emergencies in past events	UNISDR (2012)	S
-Essential infrastructure assessment	% essential infrastructures that are under regular assessment programs		S
-Accuracy of building codes	% designed structural damage – % actual structural damage (from past events)		S
-Training programs for officials	% of officials and leaders who are under regular training programs		S
-Availability of early warning centers	Average number of early warning centers per each independent zone ÷ TV		S
-Citizen disaster preparedness and response skills	Red cross training workshop participants per 10,000 persons ÷ TV	Cutter et al. (2014)	S
3-5- Recovery/ Response			
-Money dedicated to supporting the restoration	Microfinancing, cash aid, soft loans, loan guarantees available to affected households after disasters to restart livelihoods ÷ TV	UNISDR (2012)	S
-Ecosystem support plans	Local government plan to support the restoration, protection and sustainable management of ecosystems services (0 or 1)	UNISDR (2012)	S
-Local institutions access to financial reserves to support	1 (there is access), 0 (no access)		S

effective disaster response and early recovery			
-Local government access to resources and expertise to assist victims of psycho-social impacts of disasters	1 (there is access), 0 (no access)		S
-Disaster risk reduction measures integrated into post-disaster recovery and rehabilitation activities	1 (if there is), 0 (otherwise)		S
-Contingency plan degree including an outline strategy for post-disaster recovery and reconstruction	1 (if there is), 0 (otherwise)		S
4- Physical infrastructure			
4-1- Facilities			
-Sturdier housing types	% housing units not manufactured homes	Tierney (2009)	D
-Temporary housing availability	% vacant units that are for rent	Félix et al. (2013)	D
-Housing stock construction quality	100-% housing units built prior to 1970	Cutter et al. (2014)	D
-Community services	%Area of community services (recreational facilities, parks, historic sites, libraries, museums) total area ÷ TV	Burton (2015)	D
-Economic infrastructure exposure	% commercial establishments outside of high hazard zones ÷ total commercial establishment	Rubinoff and Courtney (2008)	S
-Distribution commercial facilities	%Commercial infrastructure area per area ÷ TV		D
-Hotels and accommodations	Number of hotels per total area ÷ TV	Cutter et al. (2010)	D
-Schools	Schools area (primary and secondary education) per population ÷ TV		D
4-2- Lifelines			
-Telecommunication	Average number of Internet, television, radio, telephone, and telecommunications broadcasters per household ÷ TV	Pietrzak et al. (2012)	D
-Mental health support	number of beds per 100 000	Chandra et al.	D

	population ÷ TV	(2011)	
-Physician access	Number of physicians per population ÷ TV	Cutter et al. (2014)	S
-Medical care capacity	Number of available hospital beds per 100000 population ÷ TV	Cutter et al. (2014)	D
-Evacuation routes	Major road egress points per building ÷ TV	Cutter et al. (2014)	S
-Industrial re-supply potential	Rail miles per total area ÷ TV	Cutter et al. (2014)	D
-High-speed internet infrastructure	% population with access to broadband internet service	Cutter et al. (2014)	D
-Efficient energy use	Ratio of Megawatt power production to demand		D
-Efficient Water Use	Ratio of water available to water demand	Cimellaro et al. (2016a)	D
-Gas	Ratio of gas production to gas demand		D
-Access and evacuation	Principal arterial miles per total area ÷ TV	Cutter et al. (2010)	D
-Transportation	Number of rail miles per area ÷ TV	Cutter et al. (2008b)	D
-Waste water treatment	Number of WWT units per population ÷ TV		S
5- Lifestyle and community competence			
5-1- Collective Action and Decision Making			
-Authorities interdependency	Less than 3 parties are involved in the decision-making process (1), otherwise (0)		S
5-2- Collective Efficacy and Empowerment			
-Creative class	% workforce employed in professional occupations ÷ TV	Cumming et al. (2005)	S
-Scientific services	Professional, scientific, and technical hour services per population ÷ TV	Cumming et al. (2005)	S
5-3- Quality of Life			
-Means of transport	% households with at least one vehicle	Peacock et al. (2010)	S
-Safety	1-Crime rate	Sherrieb et al. (2010)	D
-Quality of homes	Sustainability rating systems (LEED, BREEAM) ÷ maximum index number		S
-Quality of neighborhood	Sustainability rating systems (LEED, BREEAM) ÷ maximum index number		S

6- Economic development			
6-1- Financial Services			
-Hazard insurance coverage	% housing units covered by National Insurance Program	Cutter et al. (2014)	S
-Crop insurance coverage	Lands areas which are covered by Crop insurance program ÷ total area of cultivated lands	Cutter et al. (2014)	S
-Financial resource equity	Number of lending institutions per population ÷ TV	Birkmann (2006)	S
-Tax revenues	Corporate tax revenues per 1,000 population ÷ TV	Sherrieb et al. (2010)	S
6-2- Industry-Employment Services			
-Employment rate	% labor force employed ÷ TV	Sherrieb et al. (2010)	S
-Business size	% large businesses	Rose and Krausmann (2013)	S
-Professional and business services	1-% population that is not institutionalized or infirmed	Rubinoff and Courtney (2008)	D
-Economic stability	% employment rate	Burton (2015)	D
-Economic diversity	% population not employed in primary industries ÷ total employed population	Cutter et al. (2010)	S
-Households insurance	% households covered by National Insurance Program policies		S
-Research and development firms	Number of research and development firms ÷ TV	Cumming et al. (2005)	S
-Business development rate	Business gain /total business	Sherrieb et al. 2010)	S
6-3- Industry- Production			
-Food provisioning capacity	Food security rate	Pingali et al. (2005)	D
-Large retail-regional/national geographic distribution	Large retail stores ÷ total number of stores	Rose and Krausmann (2013)	S
-Local food suppliers	Farms marketing products through Community supported Agriculture per 10,000 persons ÷ TV	Berardi et al. (2011)	S
-Manufacturing	Mean sales volume of businesses ÷ TV	Rose (2007)	S
7- Social-cultural capital			
7-1- Child and Elderly Services			
-Child and elderly care programs	1 (if there is a program), 0 (if no)		S

7-2- Commercial Centers			
-Social capital-civic organizations	Number of civic organizations per population ÷ TV	Sherrieb et al. (2010)	S
-Commercial establishments	Area of commercial establishments per population ÷ TV	Rubinoff and Courtney (2008)	S
7-3- Community Participation			
-Pre-retirement age	% population below 65 years of age	Morrow B. (2008)	S
-Non-special needs	% population without sensory, physical, or mental disability	Davis and Phillips (2009)	D
-Political engagement	% voting age population participating in presidential election	Sherrieb et al. (2010)	S
-Female labor force participation	% female labor force participation	Cutter et al. (2010)	S
-Population participating in community Rating System	% population participating in Community Rating System (CRS)	Cutter et al. (2010)	D
-Emergency community participation	% community participation in case of warning systems	UNISDR (2012)	D
7-4- Cultural and Heritage Services			
-Cultural resources	National Historic Registry sites area per population ÷ TV	Rubinoff and Courtney (2008)	S
7-5- Education Services/ Disaster Awareness			
1-English language competency	% population proficient English Speakers	Hilfinger Messias et al. (2012)	S
2-Adult education and training programs	Number of yearly adult education and training programs per population ÷ TV	Burton (2015)	S
3-Education programs on DRR and disaster preparedness for local communities	Number of education programs on DRR and disaster preparedness per each local community by local government per year ÷ TV	UNISDR (2012)	S
4-Integration of disaster risk reduction in educational curriculum	Number of courses in disaster risk reduction as part of the educational curriculum per schools and colleges ÷ TV	UNISDR (2012)	S
5-Citizens awareness of evacuation plans or drills for evacuations	Average number of maneuver per institution ÷ TV		S
7-6- Non-Profit			

Organization 1-Social capital-disaster volunteerism	Red cross volunteers per 10,000 persons ÷ TV	Cutter et al. (2014)	D
7-7- Place Attachment -Social capital-religious organizations	Persons affiliated with a religious organization per 10,000 persons ÷ TV	Sherrieb et al. (2010)	S