



Spatiotemporal Pattern of Social Vulnerability in Italy

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Abstract Evaluation of social vulnerability (SV) against natural hazards remains a big challenge for disaster risk reduction. Spatiotemporal analysis of SV is important for successful implementation of prevision and prevention measures for risk mitigation. This study examined the spatiotemporal pattern of SV in Italy, and also analyzed socioeconomic factors that may influence how the Italian population reacts to catastrophic natural events. We identified 16 indicators that quantify SV and collected data for the census years 1991, 2001, and 2011. We created a social vulnerability index (SVI) for each year by using principal component analysis outputs and an additive method. Exploratory spatial data analysis, including global and local autocorrelations, was used to understand the spatial patterns of social vulnerability across the country. Specifically, univariate local Moran's index was performed for the SVI of each of the three most recent census years in order to detect changes in spatial clustering during the whole study period. The original contribution of this Italy case study was to use a bivariate spatial correlation to describe the spatiotemporal correlation between the three annual SV indices. The temporal analysis shows that the percentage of municipalities with medium social vulnerability in Italy increased from 1991 to 2011 and those with very high social vulnerability decreased. Spatial analysis provided evidence of clusters that maintained significant high values of social vulnerability throughout the study

periods. The SVI of many areas in the center and the south of the peninsula remained stable, and the people living there have continued to be potentially vulnerable to natural hazards.

Keywords Bivariate Moran's index · Cluster analysis · Italy · Natural hazards · Social vulnerability

1 Introduction

Reading the special report of the IPCC (2012) on *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* and the more recent *Climate Change 2014: Impacts, Adaptation, and Vulnerability* (IPCC 2014), it is evident that remarkable progress in research has been made in integrating social vulnerability, natural hazards, and climate change. Studies about vulnerability have generated a large literature that highlights how the multidisciplinary approach of this field has been widely adopted by researchers with different disciplinary backgrounds, including anthropology, geography, geology, and economics. One of the reasons for this interdisciplinary approach could be the increased need for policymakers, stakeholders, and researchers to have more information about the different components of vulnerability in order to adopt priority actions and guidelines for informed policy making (Fatemi et al. 2017) in disaster risk reduction (DRR).

The term “vulnerability” is used in different research contexts, such as food security, natural hazards, disaster risk management, public health, global environmental change, and climate change (Füssel and Klein 2006). The United Nations Office for Disaster Risk Reduction (UNISDR) defines vulnerability as “the characteristics and

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circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard” (UNISDR 2009, p. 30). This definition highlights an important step forward within disaster research towards a more exhaustive comprehension of the concept of vulnerability, which can account for the social consequences caused by a disaster event by questioning the supposed nature of a “natural disaster” (Carnelli and Frigerio 2016). The negative consequences of natural hazards are influenced by the socioeconomic characteristics of social groups, which have different abilities to react and manage the effect of natural hazard-related processes (Oliver-Smith 1999; Weichselgartner 2001; Cutter et al. 2003; Wisner et al. 2004; Adger 2006; Barros et al. 2014). Social vulnerability may be viewed as a set of overlapping differential dimensions (Alexander 1993; Cutter et al. 2003; Carnelli and Frigerio 2016) vary significantly within a community over space and time. Two main methods have been developed to assess social vulnerability: a deductive approach that follows main theoretical findings and an inductive approach derived from statistical relationships that include an extensive set of variables (Yoon 2012). Our approach is a deductive one, which considers the main theoretical findings to determine how selected variables vary within Italy over space and time.

In the disaster research literature, different factors have been identified by different authors as increasing or decreasing social vulnerability in every supposed phase of the disaster cycle. The main indicators used to assess social vulnerability can be identified as gender, age, education, socioeconomic status, public health condition, employment status, and access to resources. For example, females are usually linked to a higher rate of mortality in disaster contexts compared to males—as mentioned by Fatemi et al. (2017), the female population has lesser access to resources and information that affects their physical and mental health during and after disasters, at the same time children and elderly can be the most affected and have lots of problems in emergency and recovery phases (Bolin and Stanford 1998; Cutter et al. 2003; Wisner et al. 2004). A minority (disabled, migrant, or a social or ethnic community) can be linked to higher social vulnerability if that group is marginalized when living in more risky areas (Peacock et al. 2007; Carnelli and Frigerio 2016) or has experienced language and communication problems (Cutter et al. 2003). These disadvantageous situations can be linked to public health conditions and the availability of public infrastructure (Fatemi et al. 2017) when accessibility is at stake in the different phases of a disaster (for example, in terms of evacuation, preparedness, and recovery). It has been widely discussed how employment and socioeconomic status can influence both exposure to natural hazards and the ability to recover from a disaster (Wisner et al.

2004; Peacock et al. 2007; Carnelli and Frigerio 2016). Population density and growth are also often related to social vulnerability, which may affect evacuation difficulty (Carnelli and Frigerio 2016) or be linked to urban sprawl issues that can easily turn a hazard into a disaster (Kelman 2017).

A core thread in using social vulnerability as a conceptual framework should be the specific context of the analysis, including a hazard’s spatial distribution. Indeed, it has been noticed that social vulnerability is “context-dependent and is often associated with the degree of exposure to extreme events, and with the preparedness and resilience of individuals and social groups” (Fatemi et al. 2017, p. 219). Thus, social vulnerability is a dynamic and multidimensional phenomenon; it is necessary to assess vulnerability by taking into account spatial and temporal trends and by evaluation of how different vulnerability dimensions change over time and space.

The challenge faced by the researchers is how to quantify and operationalize this change process. Success involves finding a method by which to measure and observe change (Hinkel 2011). Many authors have pointed out that comparability is a key issue in making the notion of vulnerability effective and operational (Barnett et al. 2008; Ionescu et al. 2009; Wolf et al. 2010). Quantitative indicators are helpful to vulnerability reduction efforts. Currently, there is a growing interest in quantifying vulnerability as a tool for planning and policy making in relation to DRR (Birkmann 2013). Quantifying and mapping social vulnerability helps identify the most vulnerable areas and the baseline conditions for social vulnerability. Another advantage in the use of an indicator-based approach is its application in decision making, resource allocation, and project prioritization (Birkmann 2006). Rufat et al. (2015) stress the need to transform indicator identification from an academic exercise into a political necessity in order to better manage DRR.

An indicator-based approach is one of the best methods available to explore the concept of social vulnerability (Yoon 2012). Development of an indicator system to measure vulnerability is a very important issue to reducing the risk and the vulnerability of societies at risk. Due to the multidimensional nature of vulnerability, there is no unique methodology to define it and to reduce this concept to a single equation (Birkmann 2006; Yoon 2012; Fatemi et al. 2017). One of the techniques generally accepted to quantify social vulnerability is the social vulnerability index (SoVI) method pioneered by Cutter et al. (2003), which was used to measure the social vulnerability of U.S. counties to environmental hazards. This index considers 42 independent variables subsequently reduced to 11 components applying principal component analysis (PCA). This comparative metric facilitates the examination of the

differences in social vulnerability among counties. Many other scientists have subsequently exploited the SoVI methodology (Cutter et al. 2003) to assess social vulnerability in different places, modified to give due relevance to the context-specific local dimensions. For example, Chen et al. (2013) adapted and built the SoVI in order to measure social vulnerability to natural hazards in the Yangtze River Delta region in China. In the work of Guillard-Gonçalves et al. (2014) SoVI is integrated with susceptibility maps of earthquakes, floods, flash floods, landslides, tsunamis, and coastal erosion, thus delineating risk zones. Other applications of SoVI can be found in the works of Solan-gaarachchi et al. (2012) in the context of bushfire risk; Wood et al. (2010), who help emergency managers to identify communities at risk from the impacts of future tsunamis; and Frigerio, Ventura et al. (2016) with their assessment of the spatial relations between social vulnerability and seismic hazard in Italy.

Despite production of a large body of literature that uses the social vulnerability index, there is a lack of studies about the spatial and temporal variation of social vulnerability (Cutter and Finch 2008; Zhou et al. 2014). To address this gap, we explore the spatiotemporal pattern of socioeconomic factors that affect the Italian population's vulnerability. Given the changing context and conditions of its social vulnerability, Italy provides a valuable case study for our approach. Italy is one of the European countries with the highest probability to be hit by a disaster (Garschagen et al. 2016), which makes it essential to identify where, in time and space, the vulnerability exists and to suggest how improved policies can promote DRR. About 67% of Italian territory is in a seismic risk area, but 75% of the housing stock was not built following modern antiseismic code (Marino 2015). Mysiak et al. (2013) indicate that Italy's mountainous topography and the Mediterranean climate create numerous areas that are prone to significant flood and/or landslide risk. These hazardous zones exceed 29,500 km² or 9.8% of the Italian territory and affect more than 6600 (about 82%) municipalities. This exposure is often increased by negligence in planning. A study by Legambiente and the National Department of Civil Protection (2010) underlines the observation that in some areas dwellings or whole residential quarters were quite commonly located in floodplains or areas exposed to landslides (Mysiak et al. 2013) and 6% of the Italian population is constantly at risk. Between 1951 and 2011, 1394 people were killed by flooding, and thousands lost their homes after 55 major flood events (Lastoria et al. 2006). Italy is also one of the countries most affected by wildfires in Europe (San-Miguel-Ayanz et al. 2012) and extreme temperatures and droughts also experienced frequently often enhance the wildfire hazard. Landslides in Italy also have caused

deaths, missing persons, and injuries three times more numerous than those caused by floods (Salvati et al. 2010).

In this article, we examine the spatiotemporal characteristics of social vulnerability to natural hazards in Italy over 21 years (1991–2011). To do so, we first identify the leading drivers of social vulnerability to natural hazards throughout Italy; second, a principal component analysis (PCA) is applied and a social vulnerability index (SVI) is developed for each time period considered; and last, we test multitemporal spatial clustering to quantify the geographic and temporal variation of the SVI in the country. These spatiotemporal analyses are conducted to determine high susceptibility regions of social vulnerability, and to provide information about the appropriate allocation of prevention activities to better react to disaster events.

2 Data and Methods

The flowchart in Fig. 1 shows the relationship between the methodological stages of our research. Starting from the Italian National Institute of Statistics (ISTAT) database, the methodology consists of six principal steps:

- (1) Selection of variables and indicators for each year (1991, 2001, and 2011);
- (2) Normalization of the indicators using the adjusted Mazziotta–Pareto index (AMPI) method;
- (3) Application of PCA and the creation of SVI for each year;
- (4) Mapping of SVI for each year;
- (5) Application of Moran's index and local indicator of spatial autocorrelation (LISA) analysis; and
- (6) Application of bivariate Moran's index and LISA analysis.

2.1 Variables and Indicators Selection

Socioeconomic data in Italy in 1991, 2001, and 2011 were obtained from the Italian National Institute of Statistics (ISTAT), which is responsible for conducting Italy's decadal censuses. ISTAT used a methodology to adjust both municipality boundaries and population for 1991 and 2001 to those of 2011. The data we used are correct both from a geographic and from a demographic point of view for the three census enumeration years of investigation for all 8092 Italian municipalities (ISTAT 2016a, b). To analyze better the spatiotemporal pattern of social vulnerability (SV), common proxy variables were selected. We performed an extensive literature review based on empirical studies that focus on social vulnerability assessment and outcomes in the context of DRR. A substantial body of literature has been produced in order to explain the

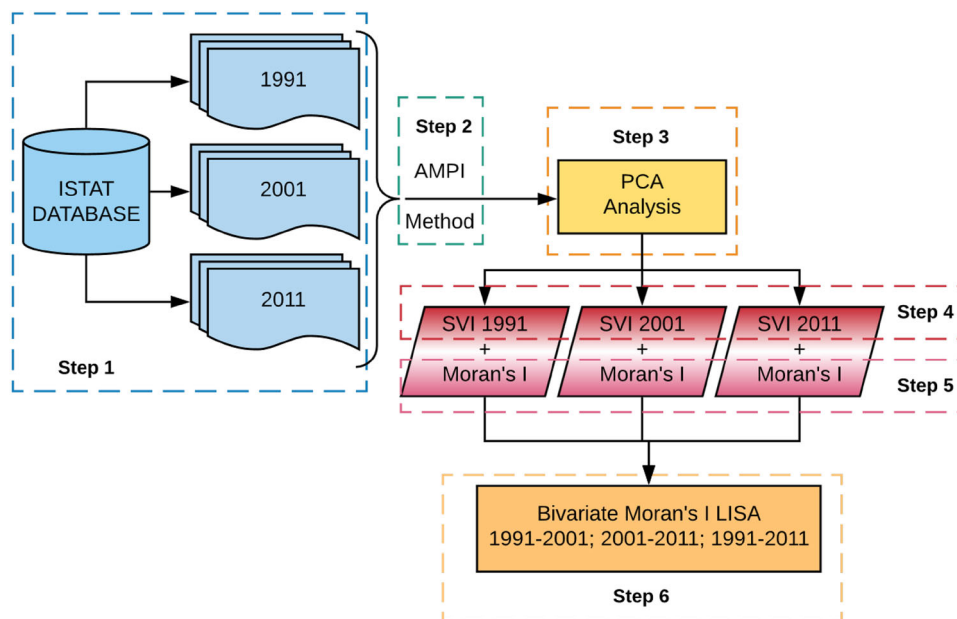


Fig. 1 Flowchart of the methodology used to study Italy's spatiotemporal pattern of social vulnerability. The first step selects variables and social vulnerability indicators starting from the Italian National Institute of Statistics (ISTAT) database. Subsequently, the indicators were normalized with the adjusted Mazziotta–Pareto index (AMPI) method in order to process them with a principal component

relationship between the selected indicators and social vulnerability (Cutter 1996; Bolin and Stanford 1998; Morrow 1999; Cutter et al. 2003; Adger et al. 2009; Oliveira Mendes 2009; Flanagan et al. 2011; Pelling and Wisner 2012). Based on this literature, all collected data were examined to identify 16 indicators that quantify SV for the study period (Table 1). Each indicator was geographically referenced based on 2011 municipality borders. These socioeconomic data cover family structure, education, housing and employment conditions, dependency ratio, and population growth, among others.

Because the original study of SoVI was conducted for the United States, many adaptations were necessary in order to apply the same methodology to the Italian context. The same main concepts were used in the search for indicators, however, and variables were chosen according to the data available in Italy and their relevance to the country's situation.

These variables represent aspects of the Italian population's socioeconomic characteristics that increase or decrease social vulnerability. Our selection reflects a compromise between data availability for the three census periods considered (the same variables for each year) and their contribution to better explain the social vulnerability of the Italian population.

analysis (PCA). Then a social vulnerability index (SVI) for each of the study's three focus years was mapped and Moran's index was applied to obtain significant clusters. Finally, bivariate Moran's I statistic was used to describe the spatial correlation between the three SVI cross section variations in time

2.2 Normalizing the Indicators Using the AMPI Method

Due to the different measurement units of indicators, data normalization is necessary in order to compare the chosen variables and compute a SVI. To appreciate absolute change over time, we used the adjusted Mazziotta–Pareto index (AMPI) method to normalize the indicators (Mazziotta and Pareto 2015). The AMPI method can be expressed as follows:

$$r_{ij} = \frac{(x_{ij} - \text{Min}_{x_j})}{\text{Max}_{x_j} - \text{Min}_{x_j}} 60 + 70$$

where r_{ij} is the normalized value of the indicator j in unit i and x_{ij} is the value of the indicator j in the same unit, i . Min_{x_j} and Max_{x_j} are the values (goalposts) calculated in order to match 100 as average for year 2001. These values were calculated as:

$$\text{Min}_{x_j} = \text{Ref}_{x_j} - \Delta$$

$$\text{Max}_{x_j} = \text{Ref}_{x_j} + \Delta$$

where $\Delta = (\text{Sup}_{x_j} - \text{Inf}_{x_j})/2$ and Ref_{x_j} is the baseline value for indicator j in 1991. Inf_{x_j} and Sup_{x_j} are respectively the minimum and maximum of indicator j for the entire period 1991–2011. In this case, the normalized values will fall approximately in the range (70–130), where 100 represents the baseline value (Table 2). This normalizing method

Table 1 Variables used in the social vulnerability index for Italy

Variables	Indicators	Impact on social vulnerability
Family with more than 6 members	Family structure	Increase
High education index	Education	Decrease
Low education index		Increase
Quality of buildings (buildings from 1972)	Socioeconomic status	Decrease
Commuting rate		Increase
Employed female labor force	Employment	Decrease
Employed labor force		
Unemployment rate		Increase
Rate of children < 14 years	Age	Increase
Rate of elderly > 65 years		
Aging index		
Dependency ratio		
Population density	Population growth	Increase
Built-up areas		
Crowding index		
Foreign residents	Race/Ethnicity	Increase

accounts for absolute change over time because normalized indicators within an identical range have much more similar variability than the original ones.

2.3 PCA Analysis and the Social Vulnerability Index

After getting a normalized indicator score for all indicators in each of the study's years, PCA analysis was applied using R software to reduce input variables and to detect the principal components for each year. The interpretation of the components has been facilitated by the application of the varimax rotation to the component matrix. Then, a positive or negative sign was assigned to the component and each of them was weighed using the percentage of variance explained (Siagian et al. 2014). Finally, a composite indicator method was used to construct the SVI for each year using the following mathematical expression:

$$SVI = \sum_i^n \pm NI_i$$

where NI is the normalized indicator considered for the computation of the index. The \pm symbol shows the direction of each NI. It was determined according to its known influences on vulnerability, which was identified from the existing literature: positive (+) directionality was given to the indicators that increase vulnerability and negative (−) directionality to the indicators that decrease it.

2.4 Mapping Social Vulnerability Indices

In order to map the geographic patterns of social vulnerability scores for each year, we classified the scores using standard deviations from the mean. Considering their frequency distribution, we used five classes with 0.5 as the standard deviation interval from the mean: very high, vulnerability > 1.5 SD; high, 0.5 SD < vulnerability < 1.5 SD; medium, − 0.5 SD < vulnerability < 0.5 SD; low, − 1.5 SD < vulnerability < − 0.5 SD; very low, vulnerability < − 1.5 SD). This classification works effectively to show data with a normal distribution. The first class includes municipalities with the highest values of the SVI, while the second to the fourth classes are more generalist and have medium and low values of social vulnerability. The last class includes municipalities with the lowest index values of social vulnerability, where socioeconomic conditions are positive.

2.5 Application of Moran's Index and Local Indicator of Spatial Autocorrelation

Following the approach developed by Anselin (1995), the Moran's index was first applied to measure the spatial autocorrelation of social vulnerability, identifying spatial clusters in the country for each single SVI map (1991, 2001, and 2011). This technique is applied to identify similar or dissimilar spatial patterns in the clustering of social vulnerability. If similar SVI values, high or low, are spatially localized, there is a positive spatial autocorrelation of the data. Otherwise, a spatial proximity of dissimilar values indicates a negative spatial autocorrelation.

Table 2 Normalized values with the AMPI method for each indicator. Mean, range, and standard deviation are shown for each time period (1991, 2001, and 2011)

Variables	1991			2001			2011		
	Mean	Range	SD	Mean	Range	SD	Mean	Range	SD
Family with more than 6 members	103.1	96.7–137.7	5.0	99.9	96.7–129.6	2.7	99.249	96.7–117.8	1.7
High education index	88.5	74.0–112.9	5.1	99.9	76.0–126.7	6.1	109.7	85.9–130.5	6.4
Low education index	103.9	94.3–109.4	1.8	99.9	88.0–107.6	2.2	96.9	88.1–104.9	2.3
Quality of buildings (buildings from 1972)	96.9	79.8–135.3	7.4	100	79.8–139.8	9.2	103.4	80.0–139.7	10.8
Commuting rate	96.6	74.5–124.2	9.1	100	74.5–126.9	9.7	103.4	74.6–134.5	10.3
Employed female labor force	95.8	74.6–120.4	8.1	99.9	76.0–127.1	8.7	103.9	80.3–129.7	8.1
Employed labor force	98.2	72.2–122.5	8.5	100	73.0–127.4	8.5	102.1	76.8–126.1	7.6
Unemployment rate	105.0	91.2–144.5	10.6	100	91.2–135.8	7.6	100	91.2–125.9	5.4
Rate of children < 14 years	103.3	76.2–133.2	8.0	100	73.2–125.6	6.1	99.2	73.2–119.3	5.4
Rate of elderly > 65 years	96.9	81.9–130.2	6.6	100	83.8–139.6	6.7	101.4	83.7–138.7	5.9
Aging index	99.4	97.5–118.5	1.7	99.9	97.6–138.6	2.1	100.1	97.7–130.7	2.0
Dependency ratio	98.8	88.8–128.5	3.8	99.9	90.1–137.7	4.4	100.7	91.4–137.4	3.7
Population density	99.9	98.9–134.3	2.3	99.9	98.9–134.4	2.3	100	98.9–130.8	2.4
Built-up areas	99.2	94.2–154.2	7.3	100	94.2–154.1	7.9	100.2	94.2–154.1	8.0
Crowding index	101.6	97.7–140.8	5.2	99.9	97.7–130.5	2.9	99.5	97.7–118.9	1.8
Foreign residents	97.3	96.5–109.3	1.0	99.9	96.5–125.7	3.1	106.0	96.5–139.7	6.8

The Moran's index varies between + 1.0 and - 1.0: a value close to +1 highlights the presence of spatial clusters of high or low values, and thus a strong positive spatial autocorrelation. Differently, a value close to - 1 means that the spatial autocorrelation is negative. A value of 0 indicates a random spatial pattern. LISA statistics were used by applying queen contiguity matrix in GeoDa software (version 1.6.7)¹ to define neighbors (queen contiguity refers to corner and edge neighbors). This application allows the identification of the following types of association: concentrations of high values (high-high, HH); concentrations of low values (low-low, LL); and spatial outliers (low-high, LH and high-low, HL). To guarantee sufficient statistical power, we used a 999 randomization with a significance filter of 0.05 (Ma et al. 2015).

2.6 Application of Bivariate Moran's Index and LISA

We investigated whether the patterns of similarity and dissimilarity in the clustering of social vulnerability remained stable across the three time periods (1991, 2001, and 2011). To do this, a bivariate Moran's I statistic was used to describe the spatial correlation between the three different annual SVI. First, a global bivariate spatial correlation analysis was applied in order to calculate a single measurement of spatial correlation respectively between SVI in 1991 and SVI in 2001, between SVI in 2001 and

SVI in 2011, and between SVI in 1991 and SVI in 2011. Then, a local bivariate spatial correlation analysis was adopted to identify local patterns of spatial associations based on the LISA statistic. The standardized first-order contiguity queen neighbors were used as the definition of neighbors in our study. Significance of the test statistic was assessed with a Monte Carlo *P* value generated using 999 random permutations.

3 Results

The results of PCA are summarized in Table 3. The percentage of the total variance explained by the first four components ranges from 73% for 2011 to 75% for 1991. The first four components are the same for each year. Employment was the dominant component for 1991 and 2001. In 2011 the dominant component became age. The first four components extracted from the PCA remain consistent during the decades as well.

As highlighted in Frigerio and De Amicis (2016) and Frigerio, Strigarò et al. (2016), age and employment are the best indicators for describing the vulnerability of the Italian population. They jointly account for more than 50% of the variability in social vulnerability among the Italian municipalities.

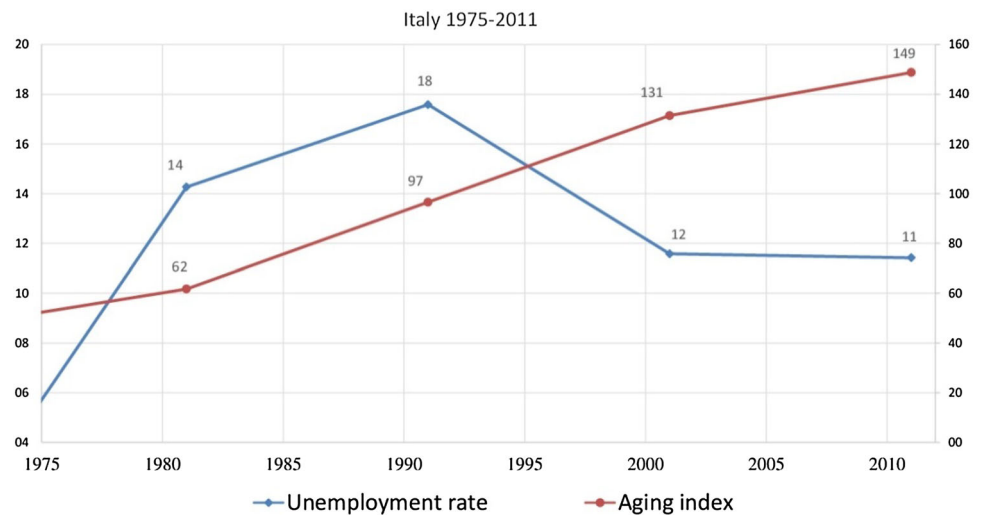
We plotted the two indicators (aging index and unemployment rate) to evaluate their different temporal trend from 1975 to 2011. Figure 2 clearly shows a significant increase of the aging index, while the unemployment rate

¹ <http://geodacenter.github.io/>.

Table 3 PCA results: the first four components and the variance explained for year 1991, 2001, and 2011

Year	PCA component	Variance explained (%)	Cumulative variance (%)
1991	Employment	28.4	28.4
	Age	26.3	54.7
	Education	12.9	67.6
	Population growth	7.4	75
2001	Employment	28.6	28.6
	Age	24.5	53.2
	Education	13	66.1
	Population growth	7.8	73.9
2011	Age	31.3	31.3
	Employment	21.4	52.7
	Education	11.8	64.5
	Population growth	8.5	73

Fig. 2 Trend comparison between unemployment rate (in blue) and aging index (in red)



had progressively decreased since 1991. This explains the reversal of the dominant component for the year 2011.

The results of geographic patterns of social vulnerability scores for each year are shown in Fig. 3. The maps indicate the geographic areas of higher potential vulnerability of a community to natural hazards.

The histogram in Fig. 4 illustrates the annual distribution of the percentage of the 8092 Italian municipalities for each social vulnerability class. It shows how the categories with extreme values of SVI (high and low vulnerability) have progressively changed. In particular, the percentage of municipalities included in the “very high” vulnerability class decreased by almost three percentage points (from 9.89 to 7.02%) over the 21-year period. The “very low” SVI class increased by almost two percentage points, confirming an improvement of general conditions. The

medium SVI classes generally increased, and a substantial number of municipalities are in the medium and lower-medium SVI categories.

To determine the patterns of similarity and dissimilarity in the clustering of social vulnerability across the three time periods, we first examined the spatial autocorrelation among the municipalities. The spatial autocorrelation of annual SVI for each year is shown in Fig. 5.

The autocorrelation clearly indicates that spatial distribution of the SVI was homogeneous in the north and the south, with a strong difference between the north and the south for the first two periods, which became more heterogeneous in 2011. Relatively high values of the SVI appeared in the southern part of the country, in the northern-eastern belt of the Italian Alpine region, and in the two main islands (Sicily and Sardinia).

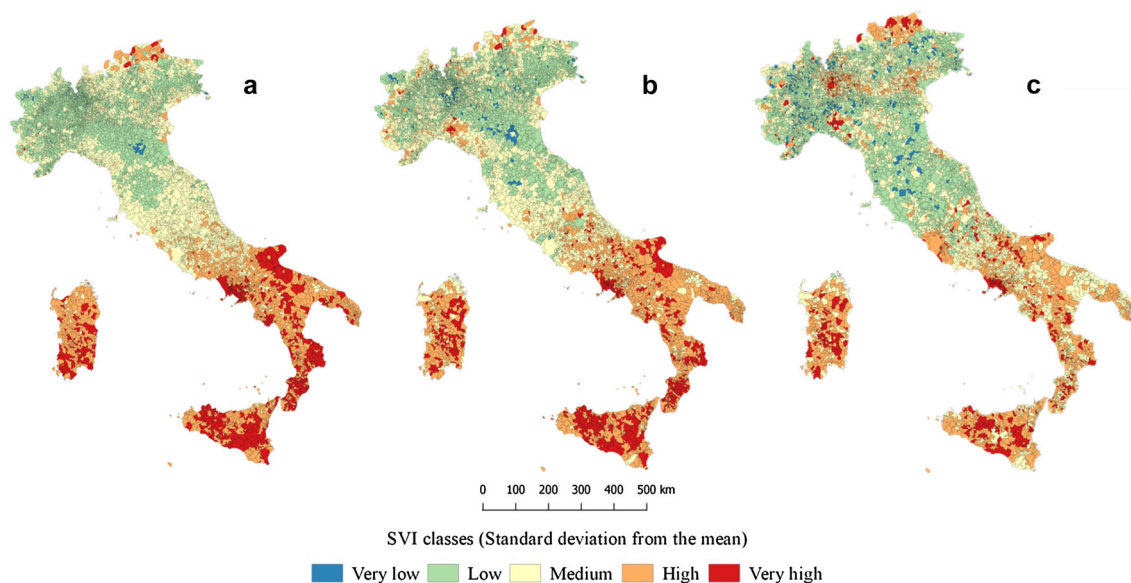
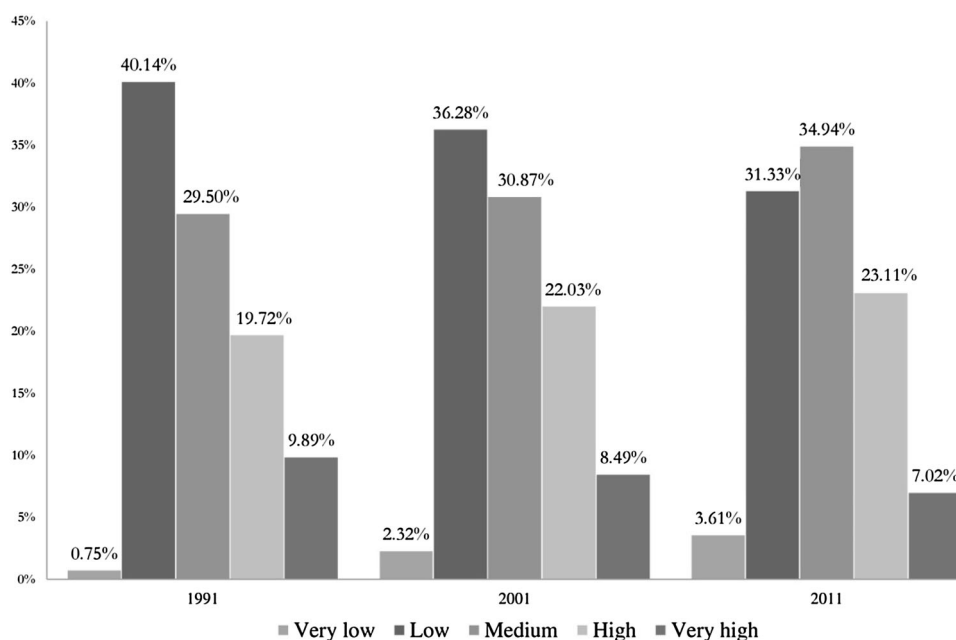


Fig. 3 Italy’s changing social vulnerability class spatial distribution: **a** 1991; **b** 2001; and **c** 2011. Very low (vulnerability < - 1.5 SD); Low (- 1.5 SD < vulnerability < - 0.5 SD); Medium (- 0.5 SD < vulnerability < 0.5 SD); High (0.5 SD < vulnerability < 1.5 SD); and Very high (vulnerability > 1.5 SD)

Fig. 4 Percentage of Italian municipalities in the five classes of SVI for 1991, 2001, and 2011



Spatial cluster analysis of the SVI identified the two most likely clusters in 1991 with a very strong global Moran’s I (0.89). The first most likely cluster included 2674 municipalities, classified as “Low–Low,” with a spatial distribution concentrated in the northwestern and central parts of the country. The second most likely cluster identified 2123 municipalities, classified as “High–High,” mainly distributed in the southern part and in a less concentrated manner in the northeastern part. Similarly, we detected the two most likely clusters in 2001 with a slight

decrease of Moran’s I (0.81). This year shows a more heterogeneous pattern of social vulnerability at the national level with a reduction of the number of municipalities in both the “High–High” cluster (2073) and the “Low–Low” cluster (2388). Finally, in 2011 (Moran’s I 0.70), the number of municipalities in the cluster with high social vulnerability values (“High–High”) (1617) significantly decreased as compared to those in the “Low–Low” cluster (2173) when compared with 2001. The 2011 SVI shows a more homogeneous spatial distribution of low vulnerability

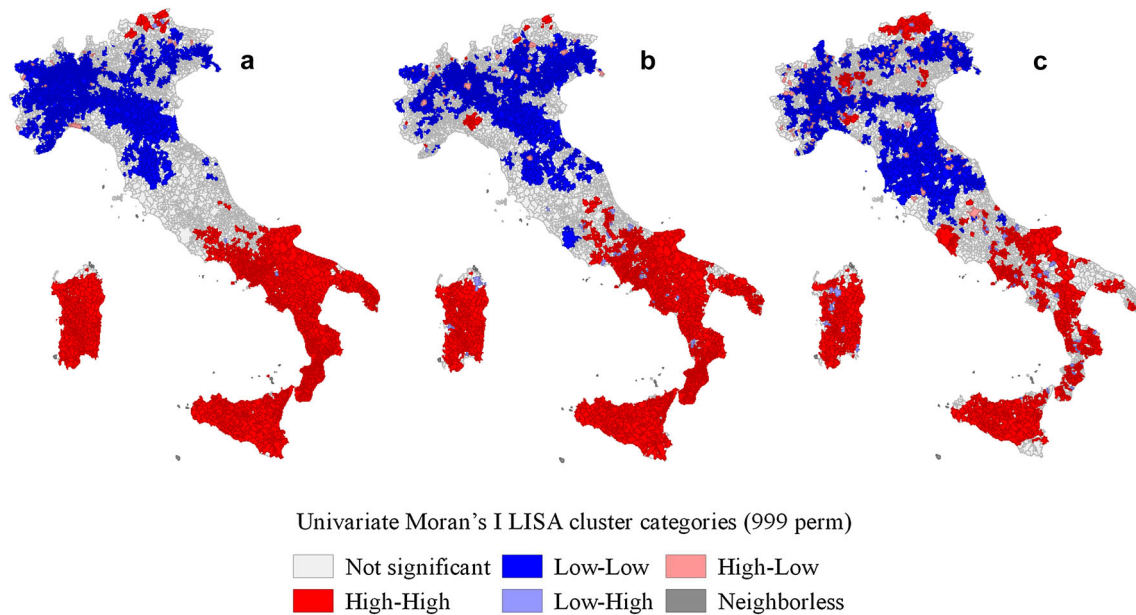


Fig. 5 Italy's changing social vulnerability as shown by univariate Moran's I LISA cluster maps for social vulnerability at the municipality level: **a** 1991; **b** 2001; and **c** 2011. Significance of the test statistic was assessed with a Monte Carlo *P* value generated using 999 random permutations

Table 4 Spatial correlation between the SVI in different years at the national level in Italy

Year	1991		2001		2011	
Univariate Moran's I	0.8859		0.8124		0.6974	
<i>P</i> value	0.05		0.05		0.05	
LISA cluster categories	Count	% of total	Count	% of total	Count	% of total
Significant local spatial clusters						
HH (High vulnerability)	2123	26.2	2073	25.6	1617	20.0
LL (Low vulnerability)	2674	33.0	2388	29.5	2173	26.9

in the northern and central areas, although concentrations of high social vulnerability remain in the southern and northwestern parts of Italy. Table 4 shows the spatial correlation among the SV indices in the different years considered at the national level in Italy. The values of the indices show a positive correlation.

The bivariate LISA cluster maps presented in Fig. 6 suggest that in the first 10 years (1991–2001, Fig. 6a) both low and high values of SVI have shown a more homogeneous spatial distribution than existed in the second time period (2001–2011, Fig. 6b). The last map, Fig. 6c, provides evidence about the geographic regions that maintained a significant positive spatial correlation (“High–High” clusters) between 1991 SVI and 2011 SVI. The hotspots are concentrated in Sardinia, Sicily, in several areas of the central-southern Apennine mountain range, and in the northeastern part of the peninsula. The results also provide evidence that a large “Low–Low” cluster

remains observable in the central and northern parts between Emilia Romagna and Tuscany regions, and in Piedmont and Friuli Venezia Giulia regions as well.

4 Discussion

In our study, the temporal analysis (Fig. 3) has shown that the percentage of municipalities with “very high” SVI values had decreased and those with “very low” SVI values had increased in the same time period. Those communities with “medium” SVI values increased at the expense of those with “low” SVI values and there is an increase in the percentage of municipalities with “high” SVI. We essentially found a shift of social vulnerability values towards the “medium” class. The highest values of SVI until 2001 can be attributed to employment conditions in southern Italy and in the two main islands (Sicily and

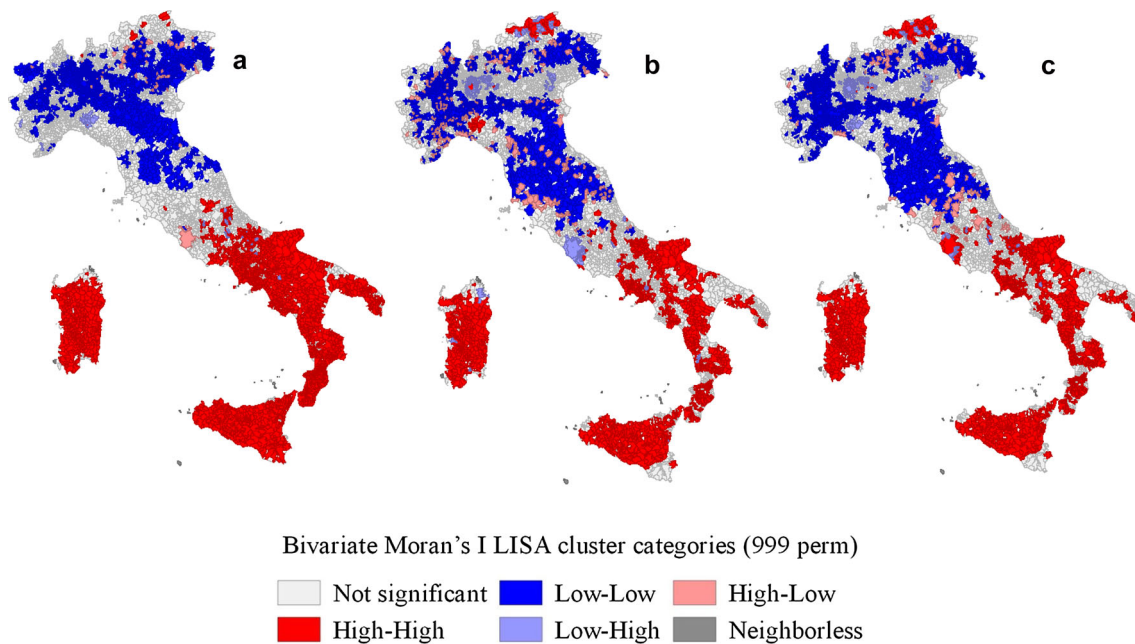


Fig. 6 Italy's changing social vulnerability as shown by bivariate LISA cluster maps of SVI in the periods considered. **a** 1991–2001; **b** 2001–2011; and **c** 1991–2011. Significance of the test statistic was

assessed with a Monte Carlo P value generated using 999 random permutations

Sardinia). The transformation of the industrial system in the 1980s led to a rapid growth of the unemployment rate in southern Italy. Since then, unemployment expansion has largely been uninterrupted. This occurred especially in southern Italy, where the highest birth rates have generated a more limited range of job opportunity compared to other geographical areas (Malamina and Daniele 2007). The unemployment rate in south Italy, unlike in the north and in the center, has risen throughout the 1990s and reached its peak in 1999, two and a half times higher than that in the north of the country in 1995, three times higher in 1998, and four times in 2004 (ISTAT 2011). This condition was consistent with the levels of development among the municipalities and coincides with their historic patterns of development. The northern municipalities received more investments than the southern regions, especially in comparison to Sicily and Sardinia (ISTAT 2011).

In 2011, 10 years later, employment conditions remained stable if compared to the aging index (Fig. 1), which increased from 131.4% in 2001 to 148.7% in 2011 (ISTAT 2010, 2011) and reached a maximum value of 238.4% in the Liguria region. For this reason, we believe that the age component has had a significant impact on the temporal trends of social vulnerability in Italy. According to the ISTAT data, since the 1970s, the Italian population became older with very low birth rates (ISTAT 2010), which explains the reversal of the first two components from 1991–2001 to 2011.

Age has been widely recognized as a driver of vulnerability (Cutter et al. 2003; Wisner et al. 2004). The elderly are particularly exposed to disaster risk. Being old often implies an isolated existence with a poor social network. The elderly are more likely to have physical and functional limitations and tend to get sick more frequently than younger people (Ngo 2012; Tierney 2006). In Italy, the rise in life expectancy during the last several decades has caused the transfer of great amounts of money from the active and economically productive age cohorts to retired people. Whether the population decreases or becomes older, this change insures that current levels of pensions and other social allowances cannot be maintained, which puts elderly citizens at higher risk when facing a disaster situation.

Another important driving force of social vulnerability in Italy that our research reveals is education, the third PCA component of the three cross sectional years. In a 2014 report, the Organization for Economic Cooperation and Development (OECD 2014) wrote that despite the positive trends in educational attainment, young Italians have lower levels of education than their peers in many other European countries. The proportion of 15–29-year-olds who were neither employed nor in education or training increased from 19.2 to 24.6% between 2008 and 2012.

Academic literature on education in the context of DRR claims that a lower educational level limits access to information and recovery assistance (Komac et al. 2010).

Educational attainment is also connected to a series of linked relationships to other social vulnerability dimensions. For example, a higher educational status often results in access to the high-skilled jobs and high socioeconomic position that usually enhances the capability of people to cope with and recover from disaster impacts.

Similarly, the fourth PCA component from remained stable for the entire period. The growing impact of population density on temporal trends of social vulnerability is evidenced by the increase of its percentage of variance explained, which changed from 7.4% in 1991 to 8.5% in 2011. This relationship is also revealed by the spatial pattern of SVI. The areas with higher population density are the big cities, particularly Milan and Naples. Rome, due to the size of the municipality, is actually less densely populated. As pointed out by Garschagen and Romero-Lankao (2015), the rate of urban population growth is more important than city size when it comes to how susceptible people are to an adverse event. Changes in population growth over time may be due to demographic and economic processes, as well as to unequal access to income and resources in society (Wisner et al. 2004).

In this study, we used bivariate spatial correlation analysis to examine the spatial relationship of SVI over time. This analysis, especially the bivariate LISA cluster map of 1991–2011, provides evidence of municipalities maintaining significantly high or low values of social vulnerability for 21 years. The SVI of many areas concentrated in the center and the south of the peninsula remained high, which suggests that people living there have been potentially vulnerable to natural hazards. These areas need to be considered as a priority for politicians, stakeholders, and policymakers in DRR efforts. This study provides an understanding of the spatiotemporal distribution of social vulnerability in Italy. Allocating more resources to high-risk locations when needed might help to reduce the probability that a natural dangerous event turns into a disaster more effectively. Our results provide evidence that, despite the global decrease of social vulnerability over time, Italy suffers a great inequality in terms of socioeconomic conditions, aging index, education, and population growth between the country's north and the south. The success of DRR strategies could benefit from giving more consideration to local social and economic conditions. Progress in the economic sector might help decrease people's vulnerability. A vicious circle exists in which poor socioeconomic conditions generally lead to a lack of access to resources, information, and education programs, and is usually associated with living in areas more at risk than better developed and endowed regions.

The results of our research could improve decision making to develop national risk-management strategies for reducing human and economic losses. To face any natural

hazard, a country needs a multidisciplinary approach and strong coordination among scientists, policymakers, and institutions. The results reached in this study can be an essential step toward addressing the issue of social vulnerability in Italy and drive disaster risk management strategies for mitigation purposes. Identifying different vulnerability clusters can lead to adjustment in practices for prevention phases and help decision makers to take the social component of vulnerability into account from a risk mitigation perspective. The concept of social vulnerability also could be incorporated into civil protection planning for emergency and recovery purposes.

A potential limit to this work is the absence of sensitivity and uncertainty analysis, a common limitation in this type of study. In a recent comparative analysis of methods to evaluate composite indicators for vulnerability in the context of DRR, only 20 of the 126 studies examined were able to conduct an explicit analysis of uncertainty or sensitivity (Beccari 2016). This inability to measure uncertainty and sensitivity should be given more consideration in future works, for example, in the application of different weights to the social vulnerability indicators, and by the estimation of errors in the resultant vulnerability scores. As mentioned by Beccari (2016), some sensitivity analyses have found significant impact of methodological choices on the resulting index values, which have implications for the broader use of these indices by policymakers. A sensitivity and uncertainty analysis of the SVI results could make a significant contribution to the robustness of the outcomes and for the implementation of these results in policy making (Schmidtlein et al. 2008).

5 Conclusion

Vulnerability is a multidimensional concept that represents complex social and cultural phenomena and explores how their interplay can lead either to a disaster or to the capability to cope with extreme adverse conditions. Mapping social vulnerability at a national scale over different time periods can inform us of changes in the sociodemographic conditions of certain places during the pre-impact phase. We believe that the production of these maps can strongly help decision making in every phase of a disaster (Carnelli and Frigerio 2016). With a cluster map of social vulnerability, decision makers can conceptually visualize the vulnerability information to other sectors to ensure that they will act in a timely and effective manner to tackle natural hazard-related losses. Our research has shown how employment, age, education, and population growth are the main indicators that lead the social vulnerability in Italy. Our methodology can offer an effective way to monitor SVI variations over time and space in Italy.

To conclude, we strongly believe that the analysis of social vulnerability must be integrated into disaster management practices in terms of political, administrative, and operational decisions. Areas identified by quantitative analysis at a large scale, showing the most vulnerable communities, need special attention and practical information obtained in the process needs to be transferred into policies in the context of prevention activities. The next step of this research will be to combine social vulnerability maps with different hazard maps in order to identify zones with high vulnerability and, at the same time, high levels of hazard (seismic, hydrogeological, volcanic, and so on) and their changing trends and characteristics over time. Indeed, time is one of the most relevant dimensions in DRR. The vulnerability approach in the disaster research literature has widely shown the processual dimension of disasters and that it is the combination of root causes, dynamic pressures, and existing unsafe conditions that turn a natural hazard into a disaster (Hoffman and Oliver-Smith 2002; Wisner et al. 2004). In the same way, time-limited planning is what usually drives politics, due to the not always immediate effects of DRR policies (Carnelli and Ventura 2015). What is really missing in Italy is a long-term and locally-coordinated political project that can adapt to, and interact with, territorial characteristics (Carnelli and Forino 2017). Social vulnerability mapping over space and time could contribute to long-term DRR policies, by identifying context-based and people-based priorities in terms of targeted risk mitigation measures.

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