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Community vulnerability to hazards: introducing local expert knowledge into the equation

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Abstract Assessments of social vulnerability have gained importance over the years, evolving from their initial emphasis on environmental factors surrounding natural disasters to a conceptual framework in which human agency plays a more decisive role. Up to know, most approaches to vulnerability were developed using an equally weighted approach in which each component contributes the same to vulnerability. To improve and enrich the information needed by authorities and stakeholders, we believe that a participatory approach would enhance our current understanding of vulnerability. Therefore, as an alternative to equally weighted approaches we propose and test the introduction of an expert panel to provide deeper insights into the relative contribution of vulnerability drivers. Our methodology has been applied to Aragón (Spain) at a municipality scale. The core of the analysis is a principal component analysis (PCA) applied to a set of socioeconomic and demographic variables. PCA allows extracting the main drivers of vulnerability in the region. Then, we introduce the role of a local expert panel by means of an analytical hierarchical process. Results are mapped and analyzed to (1) outline the spatial distribution of Community Vulnerability Index (CoVI), (2) determine the extent and location of vulnerable areas and (3) identify their main drivers. Overall, the introduction of the panel improves the ability of the method to differentiate strong (low CoVI) and weak (high CoVI) positions, compared to the original equally weighted approach.

Keywords Vulnerability index · Natural hazards · Local expert panel · Weighting approach · Aragón · Spain

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1 Introduction

Hazards, regardless of the source of origin—human or natural—are a major threat to society. The impact of hazards on human beings greatly varies over space and time, depending on several factors such as the degree of development, the exposure, the vulnerability, and the resilience of local population and settlements to a given threat (Huppert and Sparks 2006). Currently, human development is experiencing a number of singular and complex processes, altogether hindering hazard modeling (Despotou et al. 2009) such as unprecedented population growth or climate change (McBean and Ajibade 2009).

Although Spain is not among the most affected countries in the world, natural disasters are not scarce. Extreme events like floods, droughts, wildfires, heat and cold waves or earthquakes produced large human and economic losses over the last decades. Events such as the floods in Tous in 1982 or Bilbao in 1983 (Olcina Cantos 2008), the drought in the early 1990s (Olcina Cantos 2008), the 1994 wildfire season (MAGRAMA 2012) and the earthquake of Lorca in 2011 (IGME 2011) are examples of large natural disasters experienced in Spain. During the last two decades, 1215 people have died as a consequence of a natural hazard (Ministerio del Interior 2015). Specially, those events associated with floods (329 people), coastal hazards (254 people) and heat waves (178 people) stand out as the most dramatic episodes.

Aragón, the study area, has also suffered considerable losses related to natural disasters. For instance, periodic floods in the Ebro River have caused extensive economic damage. In 2015, the Government of Spain spent 24.4 million Euros in this region to restore affected areas, 1500 people were evacuated and 20,000 hectares of urban and agricultural activities were affected (Gobierno de España 2015). Moreover, flash floods provoked one of the biggest catastrophes in the history of the country when 87 people perished in Biescas (Huesca) in 1996 (García-Ruiz et al. 1996). In this sense, the main spatial planning document of the region (Departamento de Política Territorial de Aragón 2014) includes a specific chapter about natural hazards, highlighting the following characteristics of Aragón: (1) a complex territory with mountain areas, (2) an out-of-balance system of settlements, (3) low-density areas, (4) a number of municipalities in risk areas and (5) the lack of cartography of specific hazards.

Studies dealing with mitigation, prevention and planning strategies concerning hazards are now in the spotlight, being subject of analysis and discussion (Tate 2012, 2013). Indeed, this kind of analysis deserves attention, as it is a key factor for decision making, resource allocation and project prioritization (Birkmann 2006). Attempts of developing methodologies and tools to assess vulnerability and gauge mitigation initiatives are common in the literature. The United Nations International Strategy Disaster Reduction (UNISDR 2004) defines vulnerability as '*the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards*.' According to the current works on the subject, we find three main theoretical approaches to address vulnerability. Some authors support that an exposure model (Burton et al. 1993; Anderson 2000) can determine vulnerability. Others follow the assumption that vulnerability is a social condition, a measure of societal resistance or resilience to hazards (Blaikie et al. 1994; Hewitt 1997). Finally, we also find those who advocate for an integrated model of vulnerability (Kasperson et al. 1995; Cutter et al. 2000), in which both the physical environment and the socioeconomic conditions of the population are considered. Our work follows this later approach. It is based on the hazards-of-place-model of vulnerability from Cutter (1996), who gathers the biophysical vulnerability and the social vulnerability into a place or region. However, our study framed vulnerability as a broader term beyond the social dimension, pursuing the so-called community vulnerability. We believe vulnerability assessments, especially in our study region, may benefit from the consideration of access to infrastructures and services. Antwi et al. (2015) also included political and ecological aspects into their Community Vulnerability Index for Ghana.

Among the number of vulnerability indexes developed in recent years, the SoVI® approach stands out as one of the most broadly used. The method, originally formulated by Cutter et al. (2003) for the US context, is based on the use of principal component analysis (PCA) to determine the socioeconomic and demographic factors. SoVI® provides a comparative metric of the social vulnerability to a range of hazards at a given place. Several studies have been conducted following this procedure. It has been applied to a wide range of locations in the USA at several scales (Schmidtlein et al. 2008, 2011) and other regions around the world such as Norway, China, Portugal or Brazil (Holand et al. 2011; Chen et al. 2013; Guillard-Gonçalves et al. 2014; de Loyola Hummell et al. 2016). Furthermore, the United States Army Corps of Engineers (USACE) adopted this methodology for water resources planning (Dunning and Durden 2013).

In this paper, we propose a method to assess community vulnerability to hazards. The core of the analysis is a PCA. Our method considers variables beyond the social dimension, including those drivers relating communication infrastructure or proximity to medical facilities. We also consider variables from the built-in environment, which play a key role in the context of our study region (Departamento de Política Territorial de Aragón 2014).We introduced the role of a local expert panel to provide deeper insights into the relative influence of the main drivers of our index. This local expert knowledge helps to close the gap between the statistical outputs to the specificities of the territory and its inhabitants (Mustafa et al. 2011; Tate 2013). The weighting approach in vulnerability indexes has been largely left aside in the literature, adopting equally weighted schemes (Rufat et al. 2015). In this sense, Tate (2012) evidenced that hierarchical and inductive indices of social and community vulnerability are highly sensitive to the weighting approach employed. To our knowledge, this is the first attempt of weighting the vulnerability components from an inductive approach in a vulnerability index involving expert knowledge.

Participatory approaches are growing as a mean of involving stakeholders in the decision-making process on environmental issues (Dunn 2007; Goodchild 2007). Researchers and professionals around the world have pleaded for direct community participation in different stages of the mitigation plans (Buchan 2003; Roberts 2003; Becker et al. 2004; Burdge 2004). Our work falls in a midpoint between a same-weight approach and the full stakeholder participation. Thus, we decided in favor of gathering local expert knowledge to adjust our index in order to make it closer of the reality of the study region. For comparison purposes, we provided both alternatives (equally weighted and expert-weighted).

This work aims to assess community vulnerability in the municipalities of the Autonomous Community of Aragón (Spain) to hazards from a perspective that integrates the specificities of the territory and its inhabitants, so a Community Vulnerability Index (further referred to as CoVI) is presented.

The remainder of the article is organized as follows: Section 2 details the study area characteristics, while Sect. 3 describes the materials and methods used for the analysis. Results are presented and commented in Sect. 4. The discussion in Sect. 5 includes the interpretation of the results, while the conclusions and further research lines are drawn in Sect. 6.

2 Study area

The study area is the Autonomous Community of Aragón, located in the northwest of Spain (Fig. 1). This region covers 47,719 km^2, accounting for 9.4% of the national land area. Aragón is a very heterogeneous territory divided into 731 municipalities (IGEAR 2016). From the depopulated mountain areas in both the northern—Pyrenees—and the southern—Iberian System—edges of the region to highly populated urban areas in the center of the Ebro valley, we find a wide range of rural-to-urban conditions. The capital municipality—Zaragoza—holds 50.44% of the total population in 2011 (1,344,509 inhabitants; INE 2016). This kind of urban macrocephaly within such a vast territory produces very low population density values. Aragón has an average of 24.6 inhabitants/km^2, with 15 of its 33 regions below the European threshold of a demographic desert—10 inhabitants/km^2—(INE 2016). This situation produces high socioeconomic contrasts and hinders the allocation of infrastructures and services.

3 Materials and methods

The proposed method was developed in four stages (Fig. 2). The first stage comprises data retrieval from official data sources, its statistical description and preprocessing. In addition, a multi-collinearity test was conducted. In the second phase, a PCA with varimax rotation

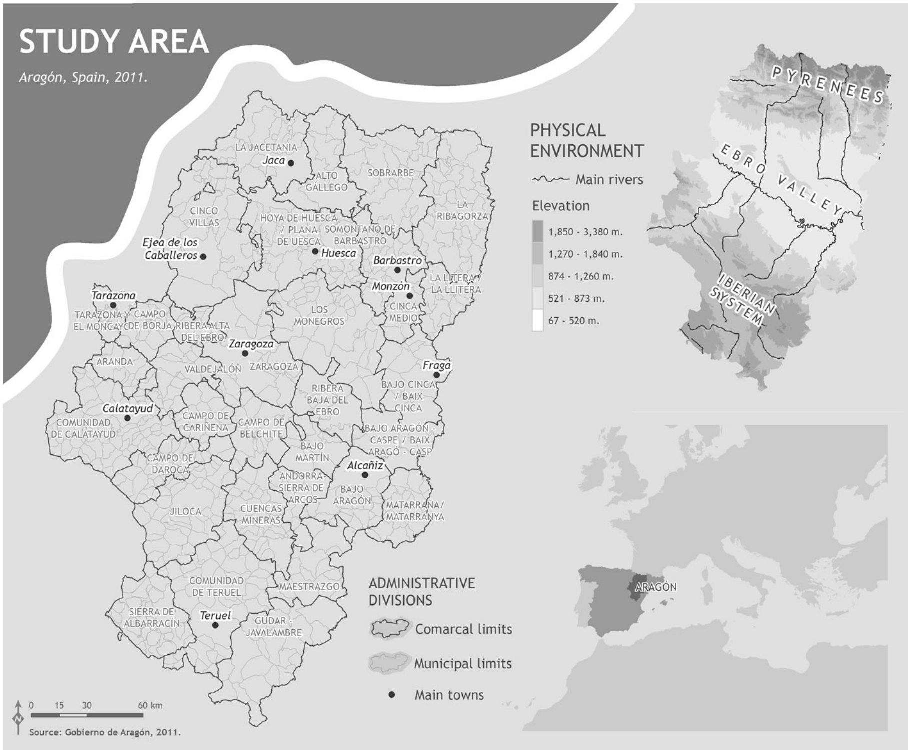

Fig. 1 Study area main characteristics: administrative limits and physical environment

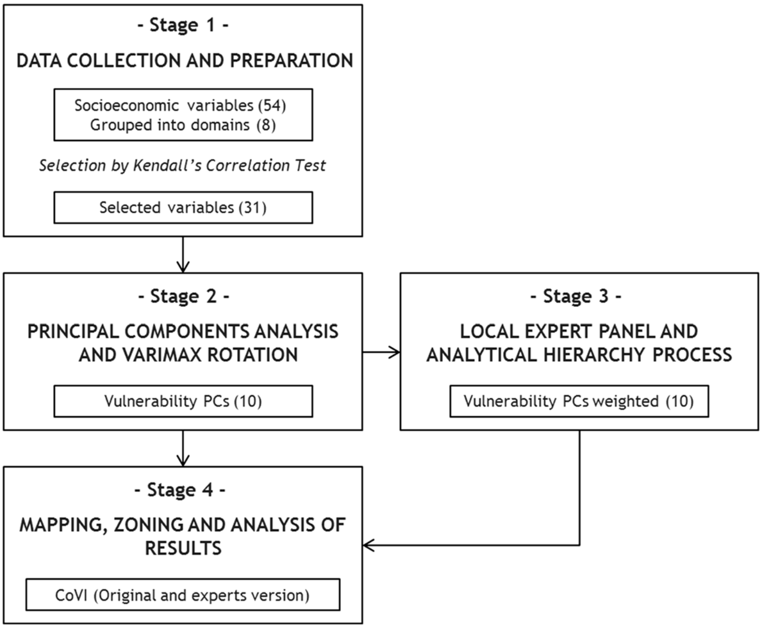

Fig. 2 Workflow followed to obtain CoVI

was performed. This allows the calculation and interpretation of key principal components (PCs). During stage 3, each PC was weighted according to the opinion of an expert panel. Weights were calculated applying an analytical hierarchy process (AHP) (Saaty 1980) to the experts' opinions. Stage 4 includes mapping, zoning and analysis of the expert-weighted and equally weighted CoVI.

3.1 Data collection and preparation

Socioeconomic data were collected from official sources for 2011, which is the reference year of the last population Census in Spain (INE 2016). The selection of the initial set of variables is based on Cutter et al. (2003), recent assessments of vulnerability in Europe (Holand et al. 2011; Guillard-Gonçalves et al. 2014), as well as recent vulnerability indexes developed in Spain (Aroca-Jiménez et al. 2016). Similar to Guillard-Gonçalves et al. (2014), variable selection had to be adapted to the context of our study area in terms of relevance and availability of data. For instance, variables relating racial or gender component, which are important in the context of the USA, are not that meaningful in Spain, whereas other factors not considered in aforementioned works turn out to be relevant in our region (population density or distance to the regional capital). In this sense, variables related to the built-in environment were included so that we consider the accessibility to infrastructures and services, paying special attention to medical care facilities. On the other hand, this study had to discard several variables, mostly in low-population municipalities. In some cases, the reason was the lack of data, while in others legal imperative—statistical secrecy—impeded obtaining information on individuals (Ley 12/1989, de 9 de mayo, de la Función Estadística Pública). The required data were retrieved from different official data sources (Table 1). The Population and Housing Census, developed and maintained by the

Table 1 Variables names and descriptions

	Name	Variable	Description	Domain	Source
1	PD	Population density	(Number of people/area in km^2)	Demography	IAEST
2	PC01.11	Population change 2001–2011	(Population change 2001–2011/ Population 2001) × 100		
3	MI	Maternity index	(Population 0–4 years/Women 15–49 years) × 100	Social dependency	IAEST
4	EDR	Elderly dependency rate	(Population 65 and older/ Population 15–64 years) × 100		
5	YDR	Young dependency rate	(Population under 15 years/ Population 15–64 years) × 100		
6	PCTFC	Percent of first category education	(Population who completed Elementary/Population) × 100	Education	IAEST
7	PCTTC	Percent of third category education	(Population who completed College/Population) × 100		
8	PCTIC	Percent of illiteracy category	(Illiterate population/ Population) × 100		
9	PCDD	Primary Care doctors density	(Number of Primary Care doctor/Population) × 1000	Medical services	IAEST
10	HCCPM	Healthcare presence in municipality	Healthcare presence in municipality		
11	PPM	Pharmacy presence in municipality	Pharmacy presence in municipality		
12	RNHD	Residents in nursing homes	(Residents in nursing homes/ Population) × 1000		
13	AI	Airfield travel time	15′ isochrones of travel time to Airfield (1 close—5 far)	Infrastructures and services	IGEAR
14	CI	Regional capital travel time	15′ isochrones of travel time to Regional capital (1 close—5 far)		
15	GHI	General hospitals travel time	15′ isochrones of travel time to General hospitals (1 close—5 far)		
16	RSI	Railway stations travel time	15′ isochrones of travel time to Railway stations (1 close—5 far)		
17	FSI	Fire stations travel time	15′ isochrones of travel time to Fire stations (1 close—5 far)		

Table 1 continued

	Name	Variable	Description	Domain	Source
18	PCIC	Per capita income category	Per capita income category (seven categories)	Wealth and patrimony	IAEST
19	RVPRHA	Rustic rateable value	Average of rustic hectare rateable value per hectare		MEC
20	TRVPUHA	Urban rateable value	Average of urban rateable value per hectare		MEC
21	RVPUBP	Urban property built rateable value	Average of urban property built rateable value per hectare		MEC
22	IBITAXPRP	Rustic property IBI tax	Average of rustic property IBI tax		MEC
23	IBITAXPUP	Urban property IBI tax	Average of urban property IBI tax		MEC
24	PCTFOR	Percent of foreign people	(Foreign people non-EU/ Population) × 100	Social attachment	IAEST
25	PCTBSM	People born in the same municipality	(Municipality-born population/ Population) × 100		
26	UR	Unemployment rate	(Unemployment population/ Economic Active population) × 100	Socioeconomic status and stability	MEC
27	VPC	Number of vehicles	(Number of vehicles/population)		DGT
28	PCTDWH	Dwellings with heating system	(Dwellings with heating system/ Dwellings) × 100		IAEST
29	PCTBNGC	Buildings in non-good condition	(Buildings in non-good condition/Buildings) × 100		IAEST
30	PCTPRID	Dwellings inhabited as principal residence	(Dwellings inhabited as principal residence/ Dwellings) × 100		IAEST
31	AVGDS	Dwelling size (number of people together)	(Average of people living together in a housing unit)		IAEST

National Statistics Institute of Spain (INE 2016), and the Municipal Registry, in this case provided by the regional Institute of Statistics of Aragón (IAEST 2016), were the main sources of information. The study also relied on data from the Ministry of Economy, Industry, and Competitiveness of Spain (MEIC 2016) and from the General Traffic Department (DGT 2016) to measure the closeness in terms of travel time to lifeline services. The base map layers were retrieved from the Geographic Institute of Aragón (IGEAR 2016).

The variables were grouped into eight domains: (1) demography, (2) social dependency, (3) education, (4) medical services, (5) infrastructures and services, (6) wealth and patrimony, (7) social attachment and (8) socioeconomic status and stability. These domains are related to the capacity of individuals to mitigate, prepare for, cope with, respond to and recover from hazards or disasters. The domains are also the basis for the interpretation of factors affecting vulnerability. Thereby, each variable is assigned to one domain according to its nature and meaning. The following lines describe in detail the main features of the domains.

(1) Demography Regions experiencing rapid population growth may lack the appropriate resources and infrastructures to absorb and adjust to the new residential load (Morrow 1999; Puente 1999; Cutter et al. 2000; Heinz Center for Science Economics and the Environment 2000). Nevertheless, we do not consider this fact to be problematic in Aragón as the population received by the municipalities has not exceeded their carrying capacity. Conversely, this factor can be a suitable indicator for the socioeconomic activity and dynamism of a region, being useful to spot decadent municipalities. Consequently, we support that the loss of population increases vulnerability. Similarly, in the context of Aragón, sparsely populated areas are seen as more susceptible than densely populated regions (Departamento de Política Territorial de Aragón 2014).

(2) Social dependency Both the children and the elderly may experience difficulties being safe in a dangerous situation. These population groups often require special attention during and after emergency events or disasters. While elderly people may suffer from mobility constraints or disabling conditions, children are dependent on parents' resources (time and economy), which, in turn, might be affected by a disaster. Higher values of dependent population are considered to increase vulnerability (Phillips et al. 2013). The social dependency domain could include disabled and dependent people regardless of their age. However, this information is under statistical secrecy in the area of study. Hence, the dependent population is determined in terms of age (children < 14 years, elderly > 65 years), which has been a recurrent approach in similar studies (Holand et al. 2011; Guillard-Gonçalves et al. 2014).

(3) Education This domain is linked to vulnerability in several aspects. First, educational attainment is likely to be related to socioeconomic status and personal wealth, as a higher degree of education often means greater income. Moreover, a lower level of education may imply a more restricted capacity of accessing and comprehending vital information about hazards, such as alerts and warnings, or safety instructions (Cutter et al. 2003; Phillips et al. 2013). Therefore, we understand that the higher the educational background is, the lower the vulnerability results. Here, when we refer to first category education, we understand it to be primary education or less (up to 12 years old), while the third category reflects any kind of university degree.

(4) Medical services Access to medical attention and services is a key factor during an emergency event. A lack of physicians, nursing homes, hospitals and pharmacies may result in larger casualties and injuries, in addition to lengthening the recovery time of the affected population (Chen et al. 2013; Phillips et al. 2013). This is especially important in Aragón, since sparsely populated areas combine with mountainous regions with poor accessibility, resulting in lengthy medical emergency response times in certain areas.

(5) Infrastructures and services The lack of accessibility to key infrastructures means a higher vulnerability of the inhabitants of those places. Lifeline infrastructures such as fire stations can significantly decrease the impact of a hazard (Cutter et al. 2003). Here, variables were introduced as isochrones (time travel by road), highlighting not only the proximity to a service but the quality and density of the road network.

(6) Wealth and patrimony Although, in terms of economic losses and property, wealthier people may suffer a higher impact than people with lower income and patrimony, we understand that those people in a comfortable situation are more likely to get themselves out of harm's way and apply measures to reduce the risk. For example, the wealthy frequently hold social safety nets and connections (i.e., policyholders). In this sense, vulnerability is estimated to be lower as income and property increase (Fothergill and Peek 2004; Cutter et al. 2009).

(7) Social attachment Segregation and social exclusion groups pose an additional challenge when facing a disaster due to the lack of social safety networks, or language and cultural barriers. Additionally, those population sectors are expected to be more vulnerable as frequently they are low-qualified workers with lower incomes (Cutter et al. 2003; Phillips et al. 2013). Aragón received more than 150,000 immigrants between the two last population censuses (2001–2011), especially from Romania, Morocco and Ecuador (INE 2016).

(8) Socioeconomic status and stability The ability to absorb and recover from disaster is strongly related to the previous status of the affected population. Employment stability and household condition, among other factors, decisively determine the vulnerability of the population.

The initial set of 31 variables is the result of a detailed exploration of the available information in official sources. To eliminate redundant information, a multi-collinearity test (Kendall's rank correlation test) was performed. Given its nonparametric nature, this test was an appropriate choice, since not all variables followed a normal distribution and some of them were categorical. A correlation threshold of ±0.7 was considered. No variables were discarded as the values of Kendall's τ-b were within the thresholds.

3.2 Principal component analysis and varimax rotation

The initial variables were standardized to Z-scores and submitted to PCA. PCs were then selected according to the Kaiser criterion—i.e., only those PCs showing an eigenvalue higher than one were kept. Next, a varimax rotation procedure was applied to reduce the number of variables to be accounted for. In order to understand the meaning of the generated PCs, variables—further referred to as drivers—with correlation coefficients higher than 0.4 were kept and analyzed in the context of social vulnerability. The spatial distribution and the sign of the relationship of a given driver and its assigned PC were analyzed. A positive sign means increased vulnerability and vice versa (Tables 2, 3). This enabled to determine whether a PC was positively or negatively related to vulnerability.

3.3 Local expert panel and analytical hierarchy process

One of the main novelties of our work lies in the use of an expert panel in order to weight PCs. Traditionally, vulnerability indexes have used equal weighting (Rufat et al. 2015). According to Tate (2013), '*equal weighting could imply equivalent importance of each indicator or recognition that there is insufficient understanding of underlying processes to assign meaningful weights*.' So far, weighting strategies have been carried out by consultation with stakeholders and experts (Hoskins and Mascherini 2009) or assigned by the index developer (Vincent 2004; Mustafa et al. 2011). In this sense, instead of solely adding the selected components or directly assigning the weights ourselves, we introduced the assessment of a local expert panel to adjust the outputs of the PCA to the specificities of the area of study. Inquired experts had extensive knowledge in fields such as spatial planning, natural hazards, civil society and geodemography in the study area, thus allowing the construction of meaningful weights.

Expert panels are used when specialized input and opinion are required (The State of Victoria 2014). We surveyed seven experts from different organizations (universities -3 experts, professional associations, research centers, public agencies and private companies) who were invited to fill in a specific design matrix (Fig. 3) combining the results of PCA. All participants were given the same directions in order to fully understand the point of

Table 2 Vulnerability: PC, percent of variance, vulnerability components, sign, dominant variables, correlation values and domain

PC	Variance (%)	Vulnerability component	Sign	Variables	Correlation	Domain
1	21.3	Educational attainment	+	PCTFC	0.543	Education
				PTCTC	−0.503	
2	7.5	Rural patrimony	−	IBITAXPRP	0.463	Personal wealth and patrimony
3	5.8	Foreign population	−	PCTFOR	−0.575	Social attachment
				PCTNSP	−0.608	
4	5.3	Medical services	−	PCDD	0.67	Medical services and access
				HCCPM	0.624	
5	4.6	Urban patrimony	+	TRVPUHA	−0.618	Wealth and patrimony
				BRVPUP	−0.539	
6	4.4	Accessibility to infrastructures and services	+	AI	0.586	Infrastructures and services
				FSI	0.588	
7	3.9	Accessibility to the capital	−	CI	−0.576	Infrastructures and services
8	3.6	Child population	+	MI	0.693	Social dependency
				YDR	0.526	
9	3.5	Mobility capacity	−	VPC	0.686	Socioeconomic status and stability
10	3.3	Precariousness	−	PTCIC	−0.492	Education
				UR	−0.541	Socioeconomic status and stability

Table 3 Expert panel results. Mean value, standard deviation and coefficient of variation of driving factor weights

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
MEAN	0.16	0.06	0.04	0.25	0.04	0.10	0.07	0.10	0.07	0.11
STD	0.09	0.06	0.02	0.06	0.02	0.04	0.03	0.07	0.03	0.05
CV	0.56	1.00	0.40	0.24	0.48	0.45	0.48	0.72	0.39	0.43

view and scope of the vulnerability factors. We paid special attention to not influence their judgment, maintaining their independence from the authors' point of view and prevent biased answers. Survey results were employed to conduct a multi-criteria analysis, so each PC is assigned a weight calculated using an AHP procedure and more specifically pairwise comparisons. AHP has been extensively used as a combined qualitative and quantitative multi-criteria decision-making methodology in multiple fields. In our case, AHP facilitated the incorporation of expert preferences by a mathematical combination of these various judgments. Thus, a weight score for each PC was obtained from every single expert. The

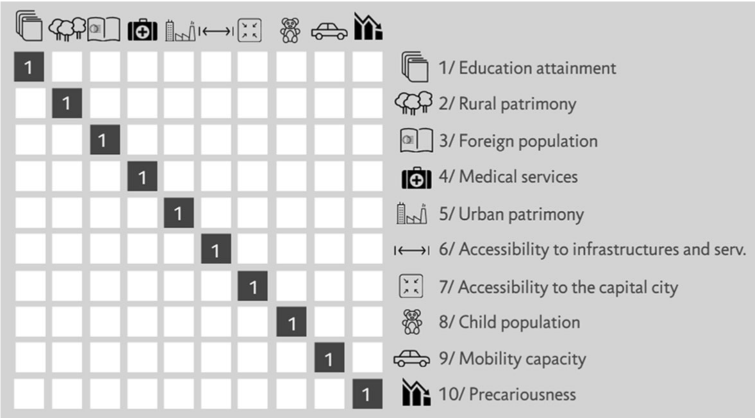

Fig. 3 AHP matrix for the local expert panel

mean of the scores bestowed by the experts to each PC constituted the final weight of the PCs. Finally, we constructed the final CoVI by aggregating the weighted PCs. Additionally, standard deviations and variation coefficients were calculated to provide insights into the dispersion of weight values according to the criteria of the panel. This allows for exploring the degree of agreement among experts.

3.4 CoVI calculation, mapping and zoning

Once PCs' weights were obtained, the Community Vulnerability Index (CoVI) was calculated and mapped. Several cartographic outputs were produced from our method. First, we mapped and analyzed the 10 PCs using a sequential scheme that organizes the selected components in terms of their explained variance. Specifically, choropleth maps were constructed using quantiles as classification method (Fig. 4). Thanks to this perspective, we analyzed the spatial patterns of the PC. Then, we calculated CoVI following the same-weight approach and CoVI applying the expert panel's weights. Equally weighted CoVI was calculated adding each PC according to its sign (increasing or decreasing vulnerability), whereas expert-weighted CoVI also included the average weighting coefficient from the AHP.

Both approaches were mapped using a diverging color scheme with gray for negative values and red for positive ones (Fig. 5). CoVI intervals were constructed from standard deviations so that we could: (1) compare the resulting spatial distributions of the indexes, (2) determine to what extent the participation process enhances the results, and (3) outline zones according to the observed vulnerability values. Furthermore, we made a final map (reclassified CoVI) splitting CoVI into three categories (Fig. 6) depending on the vulnerability position of the municipality. In this case, we use a qualitative scheme with green for strong positions, amber for intermediate positions and red for weak positions. This semiological use of color facilitates the understanding of the map. At the same time, it enhances the detection of spatial patterns and zones across the region.

As a final step, we compared weighted and equally weighted versions through an ANOVA test. Normality in index populations was addressed using the Shapiro–Wilk test (Royston 1995) after rescaling them to a 0–1 range so that their means are fully comparable. Additionally, we analyzed changes in the spatial pattern of the indexes by means of

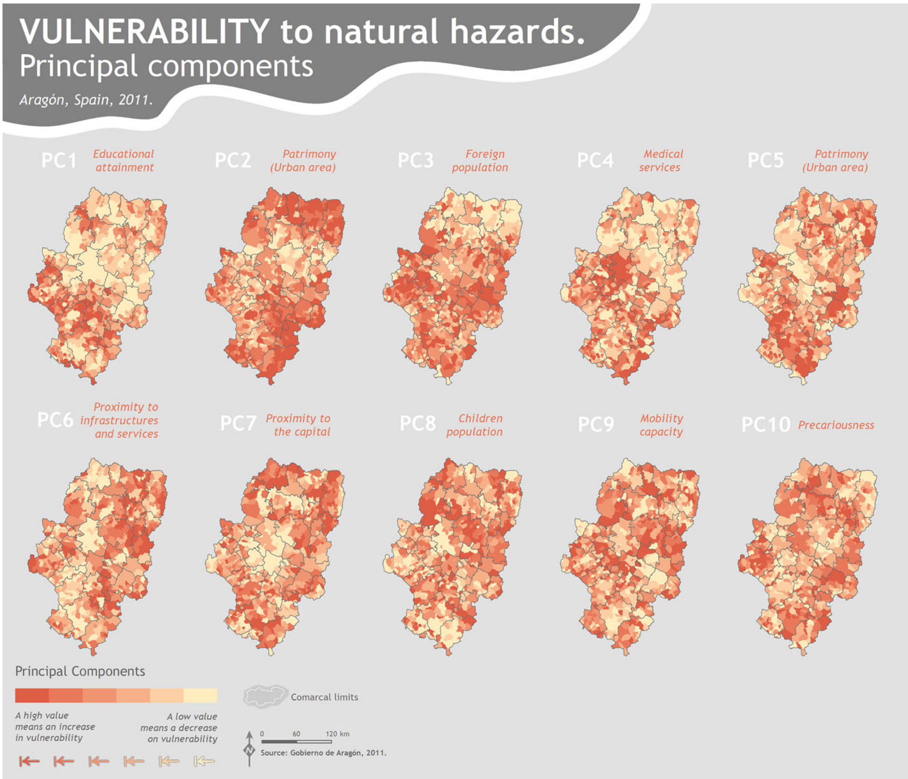

Fig. 4 Spatial distribution of principal components

cluster and outlier analysis using the Anselin's Local Moran's I (Anselin 1995). This set of stats allowed determining whether the results from both approaches were statistically different, paying special attention to their spatial behavior.

4 Results

4.1 Principal components and drivers

Ten PCs (Table 2) were selected from the PCA according to the Kaiser criterion. Overall, the selected vulnerability PCs explained 63.3% of the variance.

The *first PC* of CoVI, named 'educational attainment,' has two drivers from the education domain, explaining 21.3% of the variance. The opposite loading sign of PTCFC and PTCTC is coherent since the relation of those variables to vulnerability is opposed. Overall, this PC identifies those municipalities with lower educational attainment, and thus, it is given a positive sign. The *second PC* is named 'rural patrimony' in accordance with the dominant variable IBITAXPRP. It identifies those municipalities whose rural properties hold more economical value. This is responsible for 7.5% of the variance and receives a negative sign. The *third PC*, 'foreign population,' contributes 6% of the total variance. PCTFOR and PCTNSP, from the social attachment domain, hold a negative correlation

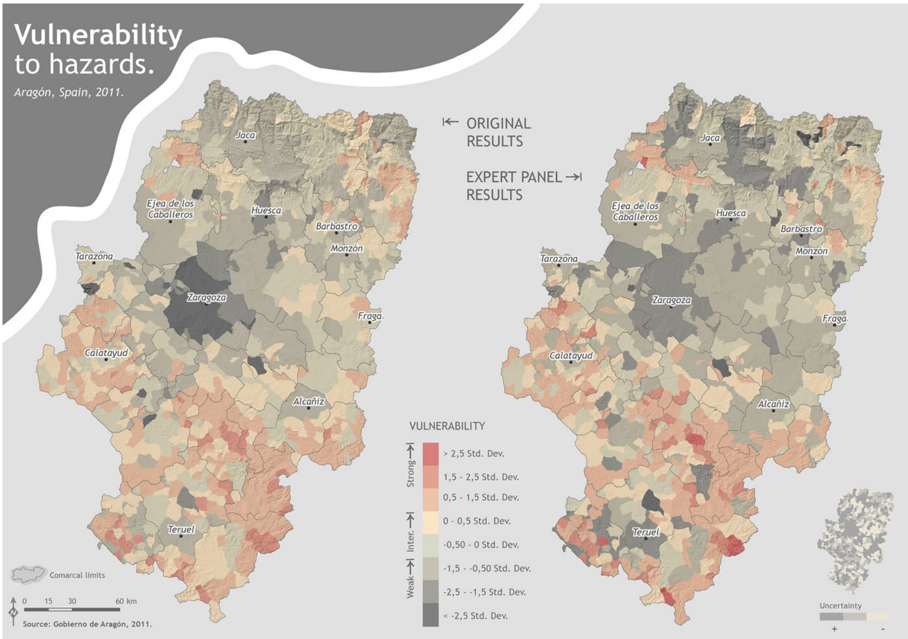

Fig. 5 Spatial distribution of CoVI

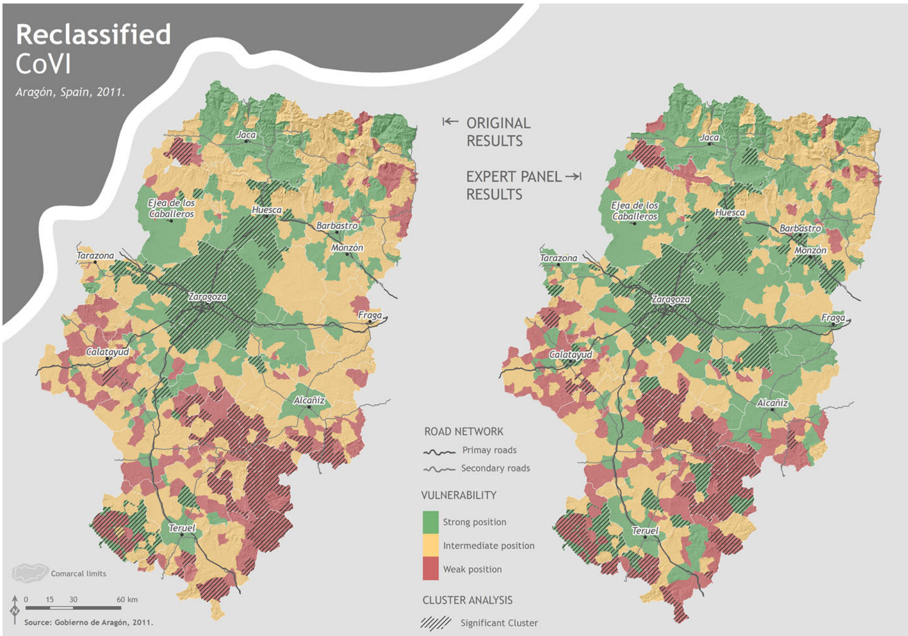

Fig. 6 Spatial distribution of reclassified CoVI and cluster analysis

with the PC. This component identifies municipalities with low percentages of foreign population. Thus, a negative sign is attributed to the PC. The *fourth PC* is 'medical services' and explains 5.3% of the variance. This factor is positively correlated with two variables from the health domain (PCDD and HCCPM). Therefore, the PC is highlighting those regions with easiest access to medical services, which reduces social vulnerability, receiving a negative sign. The *fifth PC*, 'urban patrimony,' accounts for 4.6% of the variance. It is negatively correlated with TRVPUHA and BRVPUP, from the wealth and patrimony domain. This factor gathers those municipalities whose urban land and properties present a lower value; consequently, it is given a negative sign. The *sixth PC*, named 'accessibility to infrastructures and services,' contributes 4.4% of the total variance. AI and FSI are positively correlated with the PC, meaning that this PC identifies regions with poor accessibility to services and infrastructures. Therefore, a positive sign is attributed. 'Accessibility to the capital' is the *seventh PC*, explaining 3.9% of the variance and negatively loaded due to the negative correlation sign from its driver, CI. As well as the sixth PC, this factor belongs to the infrastructures and services domain. The *eighth PC*, 'child population,' contributes 3.6% of the total variance. It is positively correlated with the drivers MI and YDR, which belong to the social dependency domain. A positive sign is therefore assigned to this PC, since it identifies municipalities with higher rates of infant population, thus increasing vulnerability. The *ninth PC* is 'mobility capacity' and explains 3.5% of the variance. Its negative sign responds to the positive correlation with the VPC variable. Finally, the *tenth PC*, 'precariousness,' accounts for 3.3% of the variance. This PC identifies municipalities whose unemployment (UR) and illiteracy (PTCIC) show low rates in comparison with the rest of the study area. For this reason, a negative sign is attributed to this PC. Figure 4 displays the spatial distribution PC.

4.2 Local expert panel assessment

Table 3 shows the weighting scores for each PC (driving factors) according to the experts' criteria. We can observe that PC4 (medical services) and PC1 (educational attainment) are the PCs that determine vulnerability the most within the study area. At the other end, PC3 (foreign population) and PC2 (rural patrimony) stand out as the least influential factors to explain vulnerability. Paying attention to the variation coefficient and the standard deviation, we can affirm that PC2 and PC8 (child population) are the PCs that generate a more diverse response from the experts, while PC4 is the one on which experts show higher agreement.

4.3 Spatial distribution of CoVI

The highest level of vulnerability (Figs. 5, 6) is located in distant and mountainous areas (Pyrenees and Iberian System), especially in the southeastern regions of Teruel (i.e., Gúdar-Javalambre, Maestrazgo, Matarraña and Cuencas Mineras), the west part of the Zaragoza province (Comunidad de Calatayud, Aranda and Campo de Daroca) and the northeast of Huesca (La Ribagorza). On the other hand, less vulnerable regions are found in the Ebro valley, especially around the capital, Zaragoza. Hoya de Huesca, Jacetania, Alto Gállego and Comunidad de Teruel also show negative standard deviation of CoVI.

Predominantly, we can observe a decrease in the CoVI scores in the expert panel version of the index compared. The spread of low-vulnerability areas is particularly noticeable in eastern Zaragoza and Huesca. Despite these differences, the main spatial patterns are similar in both indexes and the most vulnerable municipalities are located in the same areas.

According to the ANOVA outputs, equally weighted and weighted CoVI are significantly different at $p < 0.05$, being both populations normally distributed. Moreover, the spatial pattern of clustered values changes from one another. Significant clusters are mapped in Fig. 6 using a darkgray-line pattern. Two main clusters are detected by both approaches. Significant low vulnerabilities appear in the metropolitan area of Zaragoza, whereas high index values are observed in the southeast of Teruel. However, the weighted approach sharpens the shape of those clusters while also detects new cluster regions. One is located in the eastern area of Huesca, whereas smaller clusters are also spotted in some municipalities, such as Calatayud.

5 Discussion

The disparity of the spatial distribution of CoVI is the result of the historical, social, and environmental characteristics of the territory. The broad spectrum of situations (dense urbanized and industrial regions, profitable irrigation crops in rural areas, abandoned settlements in remote places, touristic regions and other poles of attraction, etc.) is reflected in the way a certain community responds to a given hazard. In this sense, the CoVI method has been developed to properly reflect this variance.

The analysis of the individual drivers of vulnerability (Fig. 4) obtained from CoVI reveals these inferences: *Educational attainment* clearly discerns the urban and more developed municipalities from the rural and traditional regions, where older population dwells. The youngest and most dynamic population migrated to urban centers, especially Zaragoza, during the 1970s and 1980s (Escolano Utrilla 2000). Industry, administration and business employment are concentrated in these areas (IGEAR 2016), so they present the highest educational attainment values. *Rural patrimony* PC shows a spatial pattern in accordance with the dichotomy between rain-fed versus irrigated crops. Thereby, rural patrimony is higher in areas near the Ebro valley, the southern and eastern regions of Huesca (Monegros, Cinca Medio, Cinca Bajo, La Litera) and some profitable crop regions—vineyards and fruit trees—in the province of Zaragoza (Campo de Cariñena and Campo de Daroca). *Foreign population* tends to be higher in rural agrarian areas, especially in western Zaragoza and in the eastern area of the three provinces. Those regions have received larger amounts of immigrants—in terms of percent of total inhabitants—in the last two decades. The *medical services* PC seems to be problematic in Zaragoza due to the amount of population living in the same municipally, not because of the lack of doctors but because of the ratio of number of doctors to assigned patients. The province of Huesca appears to be in a better situation in terms of health services, while isolated areas of Teruel (Matarraña, Maestrazgo, Gúdar-Javalambre) are deficient. The *urban patrimony* PC is higher in the most developed and urbanized regions, especially the main cities in the municipalities of Zaragoza and Huesca, and the tourist regions in the Pyrenees. The *accessibility to infrastructures and services* depends jointly on the presence/absence of such services or infrastructures in the municipality and on the road network, which allows connectivity. Therefore, once again, this PC follows consistently the pattern of the most developed municipalities and the highways that connect them. The same happens with the *accessibility to the capital* factor, particularly dependent on the road network as the city of Zaragoza is located in a central position within the region. *Child population* shows an inverse pattern compared to foreign population, which helps to understand the influence of this group in the birth rates in Aragón. According to its spatial distribution, identifying a spatial pattern for *mobility capacity* is not easy, although it appears to contribute less to vulnerability in the most developed municipalities. Finally, the last PC, *precariousness*, shows the highest values in the east region of Aragón, northwest of Huesca and the Iberian System in Zaragoza. Some of these places (especially in the east of Teruel) are inhabited by aged population, which can explain the relatively higher levels of illiteracy. In others, especially in eastern Zaragoza and Huesca, the temporality of the job market, driven by the seasonality of crops, produces a higher vulnerability of the population in these areas.

Similar results are reported in Aroca-Jiménez et al. (2016) and Guillard-Gonçavez et al. (2014). The first is based on a tree-based cluster analysis using a set of 55 socioeconomic and demographic variables. Much like our work, Aroca-Jiménez et al. (2016) address community vulnerability in an autonomous region of Spain (Castilla y León), and hence, it is particularly suitable for comparison purposes. They have identified five domains: (1) collective exposure, which gathers medical attention and education services; (2) economic development, mainly housing value and condition, and debt; (3) demographics and employment, including population structure (aging) and composition (migration), population projections toward 2025, and unemployment rate; (4) dependency, which pays special attention to child and elderly people; and (5) a highly heterogeneous fifth group combining multiple factors. The resulting domains are rather similar to ours, especially if we consider weighting the results from our panel of experts. Access to medical services and educational attainment are the main components of the first domain and are the most valuable components of vulnerability. On the other hand, Guillard-Gonçavez et al. (2014) report 38 variables grouped into seven components named: urban, age (elderly), and gender (female); development and education; nationality and ethnicity; wealth and mobility; early school leavers and health deficiency; disabled laborers; and medical access. This work was developed following the original SoVI method, so it is similar to ours from a methodological standpoint. However, in this specific case we find more differences, yet we still found similar components such as medical services and education.

With a visual analysis of the cartography of a reclassified CoVI, in its original and expert panel version (Fig. 6), we are able to summarize vulnerability into three zones. *Strong position*: municipalities with low CoVI ($\leq$0.5 sd). Within this category, we can find urban municipalities or areas connected to infrastructures and services, especially medical and education facilities. Along the Ebro valley corridor and around high-ranked towns within the urban system in Aragón (Bielza 2010), we find most of the municipalities in this group. All these areas share good accessibility by highway. Low community vulnerability appears also in the Pyrenees' municipalities with economic dynamism and resources driven by industry (Alto Gállego) and tourism (Jacetania and Ribagorza). The expert panel version enriches this pattern highlighting the influence of the communication network and economic dynamism. On the one hand, it extends strong positions to some adjacent areas. For instance, the axes Alcañiz-Caspe-Fraga, Zaragoza-Teruel and Zaragoza-Fraga, with good access to healthcare services, enter this category. On the other hand, this version restricts low-vulnerability areas in the Pyrenees to those municipalities with actual economic activity (Benasque). In this sense, strategic activities such as skiing are able to incorporate into this category spaces like Gúdar-Javalambre. *Weak positions*: high vulnerability (>0.5 sd). Several factors drive this category: lack of accessibility, elderly population and depressed economic areas. Overall, municipalities within this category are located in remote areas of the Iberian System, in the northeast of Teruel province (Andorra-Sierra de Arcos, Maestrazgo and Matarraña). Comarca del Aranda and Cuencas

Mineras appear in this category due to their decreasing industrial activity linked to footwear and mining, respectively. In addition, all these areas share an over-aged population structure and low population density. This combination of a dependant population in poorly accessible area is also found in some scattered municipalities in the province of Huesca. The abandonment of decadent rural environments during the late 1960s, 1970s and 1980s provoked this situation, which is representative of large portions of the inland Spain. Currently, authorities and policy makers try to balance the limited resources to satisfy the needs of these populations. Both equally weighted and expert panel versions agree in the overall outline of weak areas. *Intermediate positions*: municipalities with medium CoVI (−0.5 to 0.5). This category acts as a transition area, separating strong from weak positions in Aragón. From an economic and demographic standpoint, these are weak areas which are balanced due to their proximity to urban (Campo de Calatayud) or local development areas (Sobrarbe). In this case, differences are found between versions. In general lines, this is the category with the greatest extent in Aragón in the original version. However, the expert panel's version founds fewer municipalities within this category since it has a higher ability to differentiate between strong and weak positions. Intermediate positions act as a transition area between favorable and vulnerable municipalities in both cases.

The expert panel version is significantly different from the equally weighted CoVI. Moorse (2004) and Böhringer and Jochem (2007) identified weighting as one of the most subjective decisions in index construction. In this sense, Tate (2013) observed moderate differences between weighted and unweighted inductive approaches. However, Tate utilized a weighting scheme obtained from Emrich (2005), who surveyed hazard and disaster professionals, asking them to assign scores to a set of demographic indicators. This limits the comparison between our work and Tate's, as Tate's did not directly weight the components resulting from a PCA. Nevertheless, our approach also suggests moderate differences, not only in index means (ANOVA) but also in the spatial pattern. Results from cluster and outlier analysis support our previous description of the spatial distribution of strong, weak and intermediate positions and also enable to establish differences in cluster shape and distribution from one approach to another.

We have fully covered the benefits of the methodology developed in this work. However, we must recognize and contextualize its limitations. Similarly to other procedures, variable selection has to be adapted to the study area (Tate 2013). However, in order to apply our full procedure and obtain the weighting scheme, a proper set of experts or stakeholders has to be arranged. Finding an adequate number of participants may be a challenging task, especially looking at small scales. We believe this is the main drawback when using a participatory approach like ours.

6 Conclusions and further research

This paper provides a community vulnerability assessment in a heterogeneous region in southwestern Europe. The methodology combines statistical methods such as PCA and AHP with a participatory process by means of a local expert and stakeholder panel.

By introducing variables from the built-in environment, we successfully developed a community vulnerability approach for a region where the lack of accessibility is one of the most important issues in land management. Our index not only focuses on the socioeconomic features of the population inhabiting the unit areas, but on their direct and indirect needs in terms of infrastructures and services, in the event of a disaster. Moreover, the local expert panel helped to incorporate the specificities of the territory in the index. In this way, we assured that the results satisfactorily identified the most worrying factors of the community vulnerability in the area of study. In addition, weighted CoVI proved to be statistically different from the original approach, while enhancing the spatial pattern of the index.

Aragón was used as study region. Given its wide heterogeneity from both an environmental and socioeconomic point of view, significant differences in vulnerability were detected. Spatial patterns can therefore be extracted from the results. The most populated area, the central area of the Ebro valley, presents the lowest vulnerability situation. The province of Teruel, along with the southwest of Zaragoza, emerges as the region with the worst situation, as it shows large areas with high CoVI scores, especially in the mountainous regions of the Iberian System. The province of Huesca, despite its rugged relief, mainly presents a strong position as a consequence of the relative economic development in the Pyrenees and a better spatial distribution of the urban system.

Despite the difficulties that the characteristics of the study area posed (low populated unit areas), CoVI has been proven to be a valuable and satisfactory solution to better inform authorities and stakeholders making decisions on disaster risk reduction and resource management. We are able to identify the priority areas in terms of vulnerability, as well as diagnose the main drivers. Thus, CoVI can guide policy and decision makers in both 'where' and 'how' design and apply mitigation efforts.

Further research could frame the degree of community vulnerability of Aragón in a broader context (Spain or Europe). Additionally, we think downscaling our study to a more detailed scenario (metropolitan area or major cities at census areas or blocks) could reveal vulnerable areas veiled by the current scale of the study. In addition, a multi-temporal application of CoVI would also help to understand the dynamics in vulnerability during recent decades, helping to foresee the likely evolution of vulnerability.

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