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SOCIAL VULNERABILITY ANALYSIS AT MUNICIPAL LEVEL: CASE STUDY OF THE PROVINCE OF CHLEF, ALGERIA

Abstract: This paper explores the empirical assessment of social vulnerability in the Algerian context using the Social Vulnerability Index (SoVI). The SoVI is applied at the municipal level in the province of Chlef. The assessment aims to map the geographical variability of social vulnerability for the 35 municipalities of the study area. While following the original SoVI methodology, some adjustments were made to the variables to adapt them to the context. Principal Component Analysis (PCA) was performed on a set of 40 selected variables resulting in six vulnerability factors. After assigning a sign (negative, positive, or absolute) to each factor, they were summed to calculate the overall SoVI score. The resulting maps highlight the most vulnerable municipalities in the province, and their interpretation was aided by geographical maps depicting the natural and human characteristics of the territory.

Key words: social vulnerability maps, SoVI, Algeria, Province of Chlef, municipal level

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Introduction

The increasing severity and frequency of modern-day disasters is a real concern for governments and decision-makers (Ciurean et al., 2013). Two phenomena are held responsible for this situation: the climate change (Birkmann et al., 2016), and the complexity of human settlements and development (Lavell & Maskrey, 2014). As an adaptation to this reality, our understanding of disaster risk has evolved to include new concepts as vulnerability and social vulnerability. Disaster risk is described as the combination between the hazard and the characteristics inherent to the community or the place. These characteristics are gathered under the broad concept of vulnerability (Alexander, 2012). The latter is associated to various underlying aspects, among which the social vulnerability that gained the interest of decision-makers and academics. The importance of social characteristics can be observed before and during the hazard impact, and afterward during the crisis and recovery phases. The Sendai framework emphasizes social aspects and places the social vulnerability as a key factor of risk management (UN- Sendai, 2015). Wisner defines social vulnerability as: "The characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard" (Wisner et al., 2004). While all dimensions directly contribute to the overall level of vulnerability, social vulnerability has the particularity to trigger all the other forms by generating pressure on the community. Gilbert C. describes the disaster as a combination between external forces and social vulnerability (1991, cited in Blanchard, 2007). Several conceptual frameworks dedicated to disaster risk, represent social vulnerability as an aggravating condition that, besides its direct impact on risk level, has an indirect influence on all risk factors (Birkmann, 2013). Hence, the understanding of social vulnerability is necessary in order to anticipate all conditions that may increase or decrease risk factors like exposition to hazards, sensitivity, coping capacity and relief capacity.

An effective risk reduction strategy must be founded on a comprehensive understanding of vulnerability and its geographical distribution. This has led to an increased interest in the development of empirical measurement tools capable of producing comparable values and providing mappable results. As the concept of vulnerability has evolved to encompass multiple dimensions, there has been a growing need for metrics to assess each dimension among academics and risk managers. However, early assessment approaches focused more on structural and human vulnerability. The main reason for that lies in their quantifiable nature, suitable for empirical and analytical engineering approaches. In contrast, expressing social vulnerability in quantitative terms is more challenging (Cutter et al., 2003). Consequently, despite its undeniable importance, social vulnerability did not initially receive significant attention in terms of empirical studies. However, recent efforts have been made to quantify social vulnerability using approaches similar to those employed for structural vulnerability (Tate, 2012). Over the past two decades, a range of empirical methods have been proposed, one of which is the Social Vulnerability Index (SoVI) developed by the Hazards and Vulnerability Research Institute at the University of South Carolina under the direction of Susan Cutter.

When it comes to empirical assessment of social vulnerability, the SoVI is one of the most used and widely accepted metrics in the academic field (Dunning & Durden, 2013). It was initially developed in 2000 for the assessment of social vulnerability to environmental hazards in the context of the United States at the county level (Cutter et al., 2003). The SoVI has since been used and tested for a variety of hazards, at different contexts and scales, and for various purposes (Chen et al., 2013; Guillard-Gonçalves et al., 2015; Schmidtlein et al., 2008; Tate, 2012). The popularity of the SoVI can be attributed to its numerous advantages. This metric provides an objective empirical estimation, enabling the classification of communities based on their level of social vulnerability and the identification of the most vulnerable areas. The quantitative results generated by the SoVI are highly suitable for mapping social vulnerability, offering a comprehensive representation of its geographical variation within a given territory. Additionally, the SoVI proves practical in terms of data requirements. Instead of requiring specific datasets, this tool is designed to utilize commonly available statistical data on demographics, housing, and socioeconomic conditions. For most countries, such data is readily accessible and regularly updated through national census operations and similar surveys. This not only simplifies the data collection process but also makes the SoVI a flexible metric applicable on a global scale. Although being initially developed for the United States' data structure, the SoVI has been used in many countries, which demonstrates its flexibility. Despite differences among countries, the SoVI can be adjusted to suit diverse contexts and accommodate different data structures, enabling comparisons of social vulnerability on a global scale.

Vulnerability studies in Algeria

In Algeria, the situation closely mirrors the broader context of social vulnerability analysis. The country is exposed to numerous natural and technological risks. It experienced many disasters and adapted its prevention strategy over the years; notably, after two deadly disasters: the floods of Bab El Oued in 2001 and the earthquake of Boumerdes in 2003. In reaction, the country followed the new trends of risk reduction and adopted a strategy oriented toward vulnerability reduction and spatial planification (Loi 04-20, 2004). This transition required adapted procedures for analyzing and mapping vulnerability. To support the new strategy with suitable methods, various studies were conducted by both academics and government institutions (Boukri et al., 2018; Senouci et al., 2013). However, most of these studies primarily focused on physical vulnerability, with limited consideration for social characteristics as aggravating factors. Social aspects were typically discussed in term of post-disaster losses and consequences. Furthermore, following the tradition of physical vulnerability analysis, most studies concerned the urban level, despite the need for vulnerability analysis at upper levels. This is particularly important given the recent recommendations of the national risk management strategy, which emphasizes territorial analysis at the provincial level before addressing urban-scale risk assessment and management (Di Salvo et al., 2019). A study conducted in the province of Boumerdes explored the relationship between social and physical vulnerability using empirical methods (Sehili et al., 2022). However, the indicators used in that study were derived by deductive approach from sets of variables selected for different contexts, while the use of locally specific data is important to insure the relevance of the indicators to the context.

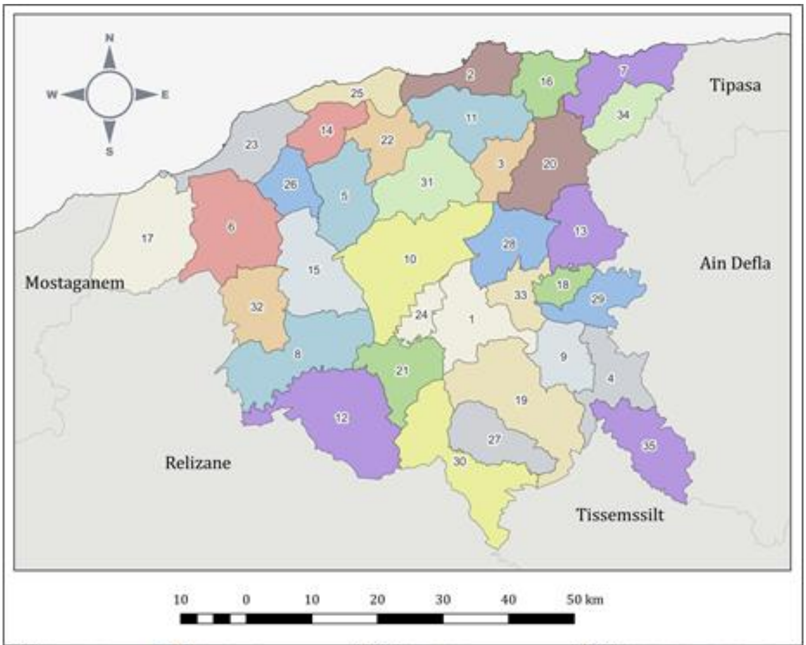
Considering the aforementioned elements, there is a compelling need to incorporate social vulnerability analysis into Algeria's risk management strategy. In this regard, the Social Vulnerability Index (SoVI) offers a convenient solution due to its ability to produce comparable and mappable outcomes, using readily available census data. The province of Chlef, chosen as a case study, has endured significant natural disasters and has been subject to a significant number of studies, but has never undergone an in-depth social vulnerability analysis. The present paper explores the social vulnerability analysis in the Algerian context. The desired analysis aims to capture and map the geographical variation in social vulnerability. It should support decision-making concerning disaster risk reduction. The SoVI is the measurement tool adopted to carry out this study, considering its convenience for the objectives and the possibility of replication. Thus, the study aims also to test the adaptability and the applicability of the SoVI in the particular context of Algeria, more specifically for the municipalities of the province of Chlef. The main social factors that determine social vulnerability are identified and combined in a single value. The resulting maps should give a comprehensive representation of social vulnerability distribution for the province. The map's interpretation is performed based on natural and human geographical characteristics. Hence the interpretation becomes intuitive for knowledgeable decision-makers as well as for the general public; allowing for more awareness about social vulnerability and better risk management.

Method and Data

Study area

The study area corresponds to the province of Chlef, located in the northwestern part of Algeria. The province counts 35 municipalities covering a total area of 4074 square kilometers (Figure 1). It's the seventh most populated province of the country, with more than a million inhabitants, spread over a territory threatened by several natural and human-induced hazards. The main economic sectors are agriculture and services, with some industrial sites. The province lies between the major mountain range of the Tellian Atlas in the South and the Mediterranean Sea in the North. The territory of the province is exposed to several hazards: flood, landslides, wildfires, and earthquake hazard which represents the greatest threat.

Because of its location in the western Mediterranean region, the province is exposed to substantial seismic activity caused by the convergence between the African and the Eurasian tectonic plates. Two major disasters testify to the threat caused by seismic activity: the Orleansville earthquake in 1954 with a 6.8 magnitude and 1500 human deaths; and the El Asnam earthquake in 1980, with a magnitude of 7.3, causing about 3000 deaths. Back to the antic period, a seismic disaster is suspected to be the cause of the destruction of the Roman city of Castellum Tingitanum, which occupied the present location of the city of Chlef (Cartier & Colbeau-Justin, 2012).



3	Benairia	12	Boukadir	21	Oued Sly	30	Ouled Benabdelkader
4	El Karimia	13	Beni Rached	22	Abou El Hassen	31	Bouzghaia
5	Tadjena	14	Talassa	23	El Marsa	32	Ain Merane
6	Taougrite	15	Herenfa	24	Chettia	33	Oum Drou
7	Beni Haoua	16	Oued Goussine	25	Sidi Abderrahmane	34	Breira
8	Sobha	17	Dahra	26	Moussadek	35	Beni Bouateb
9	Harchoun	18	Ouled Abbes	27	El Hadjadj		

Fig. 1. Municipalities of the province of Chlef

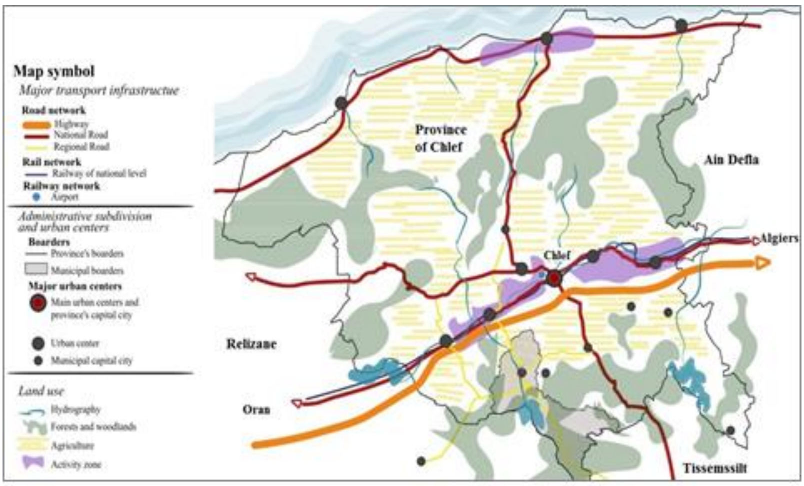


Fig. 2. Natural and human geography of the province of Chlef (Source: adapted from Di Salvo & al., 2019)

Three major natural elements are responsible for shaping the territory and creating various geographical regions in terms of physical, economic, and social characteristics, as depicted by the map in Figure 2 (Di Salvo et al., 2019). First, the plains region to the middle and the south crossed by the Chelif River, which gave the province its name. This area enjoys good accessibility due to the railway line and important highways. Many important cities are located in this region, including the chief city of Chlef. It's characterized by a diverse economic activity: agriculture due to fertile plains, important industrial parks located alongside transportation axis, and services near important cities. Second, the coastal area to the north, enclosed between the sea and the Dhahra mountains chain. Despite being linked due to the coastal national road, this area has moderate and mostly indirect connectivity with the rest of the province. The major city of this region is "Tenes", located at the junction between the coastal road and a national road connecting the south of the province to the coast. In addition to agriculture, the coastal area benefits from a commercial port and fishing resources. Finally, the area shaped by the Dahra mountains chain, which is responsible for separating the middle of the province from its coastal region. This area forms a band of highlands oriented east-west, with weak connectivity to the rest of the province.

Data

The SoVI is calculated using general census data. The most recent accessible data source is the General Census of Population and Housing (GCPH) of 2008, conducted and published by the National Office of Statistics (NOS). It covers the most of SoVI's common indicators, by direct substitution or through calculation using appropriate equations to obtain the requested values (NOS, 2011). In some cases, the modification of original set of indicators is needed in order to match with the available data. Considering the data structure of the national census, it is possible to downscale the geographical unit to the municipal level. The municipality, called "commune" in local context, is the basic administrative subdivision in Algeria. It usually counts one or more major cities within its territory. At the upper level, the country is divided into 58 provinces, called "wilaya". In each province, municipalities are grouped to form the "Daïra" that correspond to the intermediate level equivalent to the district. The province of Chlef counts 35 municipalities grouped into 13 districts.

Method

Social vulnerability is associated to a large number of variables. The SoVI development starts with an initial set of variables that is then reduced using Principal Components Analysis (PCA). The last is an exploratory data analysis method that eliminates data redundancy and filters the initial set to obtain a reduced number of indicators. The resulting set is sufficient to cover the characteristics that affect social vulnerability and its variability among the studied geographical units. Before proceeding with PCA, an adaptation process is carried out, in order to match the variables with the context, the scale and the available data structure.

In fact, when applying the SoVI outside of its original context, flexibility becomes one of its main strengths. The key of this flexibility lies in the selection process of the indicators. The variables set doesn't need to be an exact replica of the original set proposed by S. Cutter & al. (Chen et al., 2013). A research conducted by M. Schmidtlein and al. examined the SoVI sensitivity to changes in the following elements: construction procedure, scale, set of variables, and geographical context (2008). The study revealed that modifications in the set of indicators has little influence on the final results of the index and that it induces the same interpretation of social vulnerability, despite some difference in leading components and their order. For the scale changes, as well, the test showed a good stability for the final interpretation of the results.

SoVI variables' adaptation

There is no consensus about variables that can be used to measure social vulnerability (Birkmann, 2013), however, some vulnerability factors appear in most studies (Cutter et al., 2003). The original SoVI is based on a set of preselected variables grouped under a number of factors associated to social vulnerability.

In the present study, the process of variables' identification and adaptation is guided by three studies. First, it is based on the original set proposed for the United States at the county level. The set dated 2000 is regularly updated (University of South Carolina, 2023a), so we assembled variables from both the original and the current sets for the selection. In order to extend the list of potential variables, we used, as references, two additional studies, both conducted in association with S. Cutter, the main developer of the original SoVI: the study of W. Chen & al. for the Yangtze River Delta in China (2013) and the study of C. Guillard-Goncalves & al. for the greater Lisbon area in Portugal (2015).

By combining the three sets used as reference, we obtained an extended list of distinct potential variables. The list was then compared to available data and assessed for its relevance to the local context in order to be filtered and adapted. Variables that don't fit to those criteria are either eliminated or replaced by alternative variables. The alternative variables are selected with respect to their similarity to original variables or to their association with one of the vulnerability concepts of the SoVI (Table 1).

The concepts of race and ethnicity are omitted for both reasons: data issues and context convenience. Actually, in Algerian context, the link between those concepts and social vulnerability is less strong and less confirmed, in comparison to countries historically known as an immigration destination. Nevertheless, indicators related to foreign nationalities, refugees and language barrier are relevant variables in local context; they were omitted only because of the lack of data.

Extreme ages are associated to vulnerability because of reduced physical and cognitive abilities, and the dependency to assistance. Variables are selected to represent the proportion of these categories in the area, in addition to the median age that gives the tendency of the age structure. In the literature, the higher vulnerability associated to women is justified by physiological characteristics and responsibilities within the family. Situations like pregnancy or infant caring may induce additional difficulties during post-event crisis (Cutter et al., 2003). Education is a common concept of social vulnerability. Usually associated with a potential development and higher incomes, but it can also indicate good cognitive skills. In one way or another, it reflects the ability to cope with the risk and recover.

Socioeconomic status is associated to the ability to recover after experiencing losses. It is represented by indicators concerning poverty and wealth. To overcome data issues, usual variables like incomes, renters and ownership were replaced by variables about basic household appliances. Some house appliances are so affordable and democratized that their absence becomes a sign of financial difficulties. On the other hand, some properties, like cars and secondary houses, indicate wealth. Car ownership is also included in Cutter's original set under a separate concept (University of South Carolina, 2023a).

Housing is an important concept of social vulnerability assessment. Three related groups of variables are used in this study: housing condition, housing occupancy and housing type. Housing condition is associated with the physical dimension. Variables about house amenities are selected to indicate this aspect. Even though variables of this nature aren't present in the original SoVI, they are used in the sets proposed by Chen (2013) and Guillard-Gonçalves (2015). Proportion of precarious houses is added as a variable, since data is available and it has a direct link with the concept. According to Cutter S. & al., potential human and material losses are function of housing characteristics like: value, quality and density (2003). Considering data structure, the proportion of common house types in the area are added to replace similar variables proposed by the original SoVI. For house occupancy, selected variables are related to the number of occupants per unit, while variables about house tenure status and house value were omitted due to the lack of data.

Tab. 1. Selected variables for the SoVI at the province of Chlef - ✓: Identical variable; (✓): Equivalent variable

Concept	**N°**	**Name**	**Description**	**References**		
				Cutter &al. (2003	Chen & al. (2013)	Guil-lard-G. &
Age	1	QPOPUD5	Proportion of population with age <5		✓	✓
	2	QPOPAB65	Proportion of population with age >65	✓	✓	✓
	3	QPOP5-14	Proportion of resident population aged 5–14			✓
	4	QPOP15-19	Proportion of resident population aged 15–19			✓
	5	MEDAGE	Median Age	✓	✓	✓
Socioeconomic status	6	QNOTV	Proportion of households without TV			
	7	QNOREF	Proportion of households without refrigerator			
	8	QNOSTOV	Proportion of households without stove			
	9	QAFWM	Proportion of households Affording a Washing Machine			
	10	QAFSRES	Proportion of households Affording a secondary residence			
	11	QNOAUTO	Proportion of Housing Units with No Car	✓		
Gender	12	QFEMALE	Proportion of Female	✓	✓	✓
Education	13	QED12LES	Proportion of people with Less than 12th Grade Education	✓		
	14	QHIGHEDU	Proportion of population with High education level		(✓)	
	15	QUNISCO	Proportion of Population above 15 YO who are students or at school			(✓)
	16	QSCHLEAV	Proportion of school leavers			✓
	17	QILLIT	Illiteracy rate of population aged 15 years or older		✓	✓

Housing	18	QNOELEC	Proportion of houses without electricity			✓
	19	QNOSEW	Proportion of houses without sewerage			✓
	20	QNOBATH	Proportion of houses without baths or shower		✓	✓
	21	QNOWC	Proportion houses without Toilet		✓	✓
	22	QNOPIPWT	Proportion of houses without piped water		✓	
	23	QNOKITCH	Proportion houses without kitchen		✓	
	24	QNOCGAZ	Proportion of houses without City Gaz			
	25	QPRECAH	Proportion of precarious houses			
	26	PPUNIT	Number of People per Unit	✓		
	27	PPROOM	Number of People per room		✓	
	28	QUNOCHU	Proportion of Unoccupied Housing Units	✓		
	29	QSINGFH	Proportion of Single-family houses			
	30	QAPPART	Proportion of apartments			
Occupation	31	QLABRF	Proportion of labor force (People at working age >15)	(✓)		
	32	QEMPL	Employment rate among active			(✓)
	33	QHUPRO	Proportion of houses used for professional activity			
	34	QFEMLBR	Proportion of Female Partici-pation in Labor Force	✓		✓
Health insurance	35	QNOHLTH	Proportion of Population without Health Insurance	✓		
Urban/ Rural	36	QPSCAT	Proportion of population in scattered area			
	37	QPSECA	Proportion of population in secondary agglomerations			
	38	QURBAN	Proportion Urban Population	✓	✓	
Family structure	38	PHSHOLD	Average number of people per household		✓	✓
Population change	40	POPCH	Growth rate of resident popula-tion (2000–2010)		✓	✓

Most variables related to health services are not taken into consideration because of data availability issues. It's the case for variables about health care personnel. While those linked to material resources are omitted because of the particular distribution and organization of health facilities in the Algerian context. In fact, important health facilities are located in major cities with several municipalities annexed to them. If the use of variables such as "the number of health facilities" and "the number of beds" is justified to compare provinces, it is not the case in this study, because some municipalities have special administrative status at the provincial or district level. Thus, health facilities located in their territories are, in fact, shared facilities for several municipalities. The remaining variable concerning health care insurance is calculated by using data about occupation, as health care coverage in Algeria is mandatory for all occupied persons.

Occupation and employment are used in the SoVI as indicators of the economic situation. There is no available data about specific sectors of occupation like agriculture, extraction, and services; therefore, only general variables are selected. They concern the labor force (population at working age ≥15), employment rate, and women's participation in the labor force. The variable "percent of houses used for professional activity" was added to the set. In municipalities with large urbanized cities, the transformation of houses for business indicates important economic activity.

Both high urbanization and rurality are associated with social vulnerability. The high density in urban areas makes crisis management more complicated; besides, urban communities are less cautious with hazard exposition because of land saturation. On the other hand, economic sectors and lack of infrastructure that characterize rural regions are responsible for socioeconomic disparity, which results in more vulnerability.

Rapid population growth, whatever its origin, puts pressure on housing, infrastructure and job market leading to the aggravation of social vulnerability. At the household level, the family structure determines the lack or the availability of financial resources, as well as familial responsibilities and dependencies affecting the ability to cope with disasters.

PCA Application

The variables selection resulted in a set of 40 variables. The PCA is applied to the 35 municipalities of the study area with the selected variables. As recommended by Cutter & al., (2003), inputs are processed first by normalization to percentages and per capita; then by standardization using a Z-Score method that transforms the data set to have a mean equal to 0 and a standard deviation equal to 1. Following the recommendations of the "SoVI Recipe" sheet (University of South Carolina, 2023b), analysis is performed with varimax rotation, which maximizes the correlation with a few significant variables; while it's minimized for the remaining ones. This makes the interpretation easier despite dealing with a large number of variables. The Kaiser criterion is applied to extract the factors. It considers as a principal component only the factors with an eigenvalue superior or equal to 1. The selected few factors have the major contribution to the total variance of the variables for the analyzed sample.

The extracted principal components are named using their underlying dominant drivers. Within each component, we consider as dominant drivers the variables with a coefficient of correlation (loading) superior to +0,7 and inferior to -0,7. Drivers with loadings superior to +0,5 and inferior to -0,5 may also be considered if needed to figure out the factors' names. A directive adjustment is applied to the factors in order to guarantee that positive values increase social vulnerability and negative ones decrease it. The adjustment is performed through the examination of the underlying indicators, their signs, and their logical influence on the tendency of social vulnerability level. In some cases, the interpretation is ambiguous because variables with the same influence on vulnerability tendency have opposite signs. In such situations, the SoVI methodology allows the use of an absolute value for the factor.

Results

SoVI's factors and calculation

The application of the Kaiser criterion revealed 6 principal components, explaining 82.9 % of the variance. Table 2 represents the extracted factors, their dominant drivers (loading under -0.7 and above +0.7), and some secondary drivers (loading under -0.5 and above +0.5). Factors are named according to their dominant drivers and if necessary secondary drivers are also used.

The first factor, named “poor housing quality and socioeconomic development” explains 27.45% of the total variance. It is represented by 9 dominant drivers among 18 in total. The main indicators of the factor are related to the poor living standards of the houses and the socioeconomic development of the community. There is no ambiguity about the cardinality of the first factor. A positive sign is affected to the factor since all drivers that increase vulnerability load positively (Table 2), like precarious housing (PRECAH +0.898) and proportion of houses lacking basic utilities (QNOWC +0.857; QNOKITCH +0.834). On the other hand, drivers that decrease vulnerability loads negatively, like labor force (QLABORF -0.665).

The second factor contributing to 21.86% of the variance is “poverty and education”. It gathers indicators representing a lack of basic house equipment and low education level. Positively loading drivers are vulnerability-increasers, like the lack of house equipment (QNOSTOV +0.892, QNOCGAZ +0.741), and low education level (QED12LESS + 0.784, QILLIT + 0.664). While vulnerability-decreasing drivers have negative loads; such as residents with high education levels (QHIGHEDU -0.793). Thus, the second factor receives a positive cardinality.

“Family size and labor force” is the third factor, with a contribution of 13.35% to the variance. Indicators describing large households and high house occupation increase vulnerability while having positive loadings. Hence a positive cardinality is assigned to the factor. This choice is compatible with the nature of the negative drivers, describing activity and wealth because they have all the influence of decreasing vulnerability.

Component number four named “land use and demographic structure” counts 4 dominant drivers and contributes to 8.15% of the variance. All of its drivers can be linked with vulnerability rise, besides the indicator QHUPRO which the influence on vulnerability may have divergent interpretations according to the level of urbanization. However, the drivers load in opposite directions, and thus neither a positive nor negative sign will make sense for the direction of vulnerability progression. Therefore, the absolute value is assigned to this factor, following the SoVI methodology.

The fifth factor related to “age” is responsible for 7.65% of the variance. It receives a negative cardinality as the drivers indicating favorable age ranges for vulnerability decrease are negative; while indicators for age ranges increasing vulnerability are positive. The inversion of the factor cardinality with a negative sign will adjust the direction of vulnerability progression.

The sixth and last principal component contributes to 4.14% of the variance explanation. It is named “housing stock” according to its dominant driver indicating the proportion of unoccupied houses. This vulnerability-decreasing indicator shows a positive load. Hence a negative sign before the factor will adjust its influence on vulnerability level.

The SoVI score is calculated for each municipality by the combination of the factors with their relative signs in an additive model. The resulting formula is as follows:

$$SoVI=F1+F2+F3+|F4|-F5-F6$$

Tab. 2. Principal components of the SoVI for the province of Chlef

N°	Component name	Sign	Number of Drivers	Variance explained (%) (Cumulative)	Dominant Drivers (Loadings) Other drivers (Loadings)
1	Poor housing quality and socioeconomic development	+	9	27.459	QPRECAH (+0.898); QSCHLEAV (-0.894); QNOWC (+0.857); QNOKITCH (+0.834); QNOTV (+0.822); QNOREF (+0.806); QNOPIPWT (+0.748); QNOHLTH (+0.746); QNOELEC (+0.742).
					... and 9 more secondary drivers
2	Poverty and education	+	6	21.866 (49.324)	QNOSTOV (+0.892); QAFWM (-0.851); QHIGHEDU (-0.794); QED12LES (+0.784); QAPPART (-0.750); QNOCGAZ (+0.741).
					... and 9 more secondary drivers.
3	Family size and labor force	+	3	13.353 (70.829)	PHSHOLD (+0.889); QLABRF (-0.799); PPUNIT (+0.798).
					QFEMLBR (-0.616); QNOSEW (+0.570); QAFSRES (-0.548); Q15-19 (+0.501).
4	Land use and demographic structure	[illegible]	4	8.152 (57.476)	QHUPRO (+0.843); QFEMALE (+0.756); POPCH (-0.726); QPOPUD5 (-0.716).
5	Age	-	1	7.654 (78.483)	MEDAGE (-0.709).
					QPOPAB65 (-0.685); Q5-14 (+0.549); QCVLUN (-0.537).
6	Housing stock	-	1	4.418 (82.901)	QUNOCCHU (+0.738).
					QPSECA (-0.650).

SoVI mapping

As recommended by the SoVI methodology for the mapping, the resulting scores are transformed into standard deviations (Figure 3). The mapping classification counts 5 levels of social vulnerability. The medium class has a SoVI standard deviation between -0.5 and +0.5. Values above are labeled as higher vulnerability and classed in two levels, high (+0.5 to +1.5) and very high (>+1.5). Values beneath the medium level represent lower vulnerability, low (-1.5 to -0.5), and very low (<-1.5).

The mapping shows that none of the 35 municipalities of the province have a very low level of vulnerability (Figure 3). Most of the province's territory falls under the medium or the low levels. The SoVI map revealed three municipalities with very high vulnerability: Dahra, Breira and Beni-Haoua, with an SoVI standard deviation superior to +1.5. A close examination of the SoVI results shows that Breira has the highest level of social vulnerability with a score of 3.1 (St. Dev.), far above the two other municipalities. The contribution of the first factor "Poor housing quality and socioeconomic development" was decisive for the high SoVI score of the three municipalities (Figure 4).

By looking at the factors maps (Figure 4) we can notice that several municipalities obtained a very high score in one of the remaining factors, but it wasn't sufficient to influence the overall SoVI score. One municipality, Beni- Bouattab, obtained a very high level in two underlying factors other than the first one (F2: Poverty and education; F4: Land use & demographic structure) and only got a high level of vulnerability. Such cases demonstrate the decisive contribution of the first factor to the overall score, in comparison to other factors. This is mainly because the two factors are outweighed by the low value of the remaining factors, which is not the case for the factor of poor housing quality and socioeconomic development.

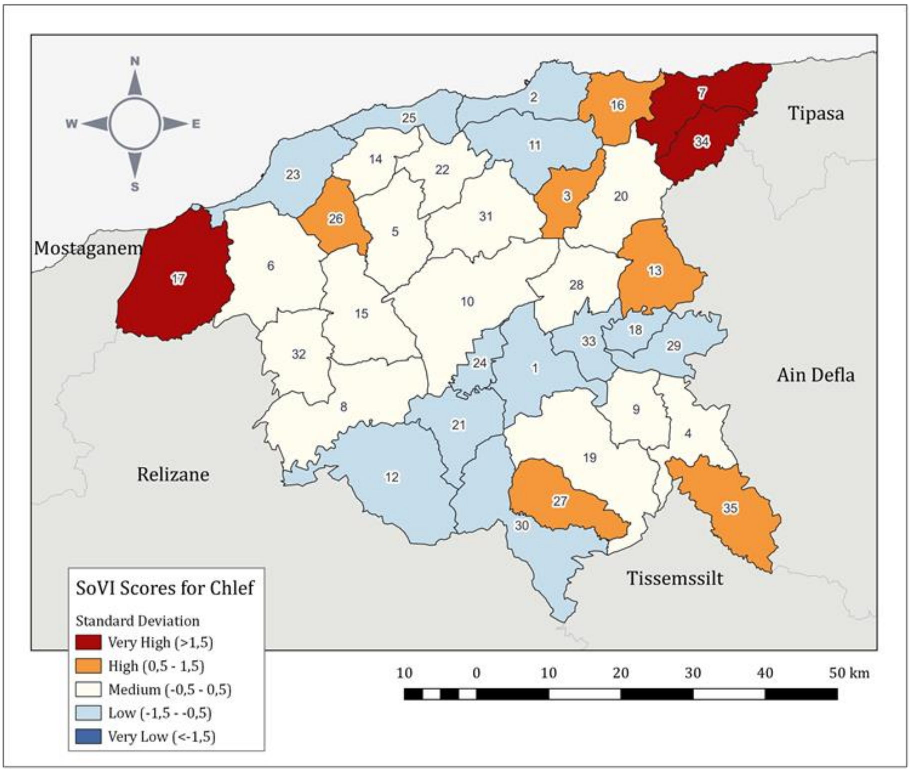


Fig. 3. SoVI map for the province of Chlef

Major municipalities with important cities, like Chlef and Tenes, exhibit a good score (low and medium) for most of the factors, particularly for the second factor concerning "Poverty and education". The factor of "age" shows less diversity with only two municipalities above the medium class: Tenes and Abou El Hassan, and seems to be less determinant for indicating the variability of social vulnerability.

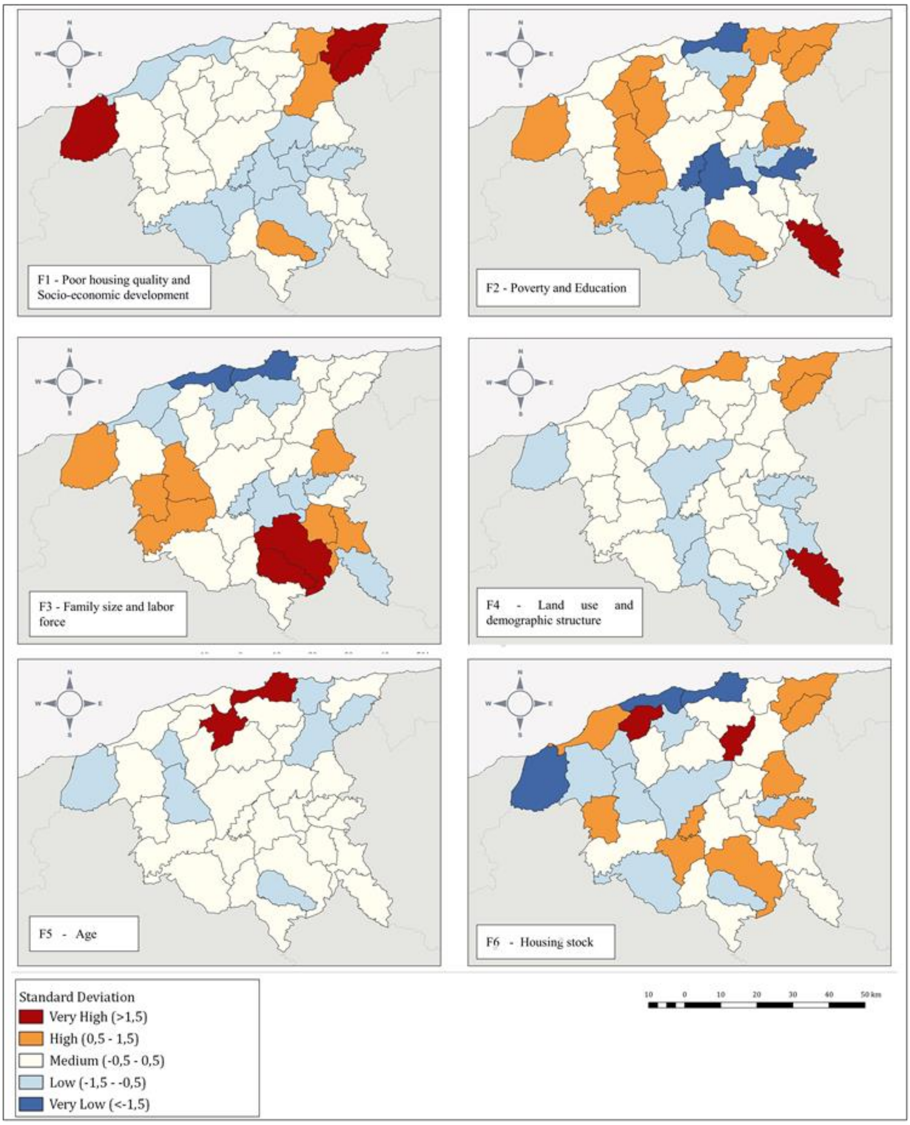


Fig. 4. Maps of the principal components of social vulnerability for the province of Chlef

Discussion

The most vulnerable municipalities, labeled as very high, are all located at the northern borders of the province. They are characterized by the following common features: the location in the coastal band, a rugged mountain landscape and weak connectivity. Municipalities labeled with a high vulnerability share some of these characteristics, like Beni-Bouattab, Beni-Rached and El Hadjadj which are located at the geographic ends of the province and present the same mountain character. Such characteristics spot geographic and economic remote regions that lack local development. With no industrial and service sectors, agriculture is the main resource for these areas. Yet, even farming in the mountain areas is less profitable compared to the intensive agricultural model adopted in the lowlands of Chelif Valley. This made the difference between some municipalities that share all characteristics apart from the agricultural model. For instance, the municipality of Ouled-Ben-Abdelkader exhibits low vulnerability, whereas Beni-Bouattab and Beni-Rached are both ranked as having a high vulnerability level, despite the only distinguishing factor being the farming model. As a consequence of this socioeconomic disparity, poverty and weak education are higher for the concerned municipalities, leading to higher vulnerability. In addition, they all suffer from the precariousness of their housing stock and the weak development of basic infrastructure and amenities.

The coastal band has a divergent pattern of vulnerability distribution, with half municipalities showing high and very high vulnerability and the other half showing low vulnerability. The region counts the three municipalities with the highest vulnerability scores in the province. In fact, despite belonging to the same geographic area, coastal municipalities have different natural and economic features. Firstly, the economy is diversified in the middle part of the coastal band, with the presence of the economic activity zone and the commercial harbor. Secondly, vulnerable municipalities at the edges of the coastal band have a larger mountainous inland area with less connectivity and more rural character.

Low vulnerability characterizes all the municipalities located along the Chelif Valley, as well as the main roads and railways of national importance. This confirms the outcomes observed for the high vulnerability categories, as the characteristics here are opposed. The relation is evident between connectivity and most vulnerability indicators: good infrastructure and less house precariousness, better education and incomes. The diversified economy of the region and its good connectivity contribute to reducing most vulnerability factors and thus, the overall social vulnerability.

The majority of medium vulnerability areas are spread between the valley and the shore. Municipalities within this area have diversified economy despite the dominance of services and agriculture over industry. Connectivity was the determinant aspect that influenced the social vulnerability in this region, as the municipalities with direct accessibility could depend on important cities in other regions. On the other hand, the few municipalities of the area that are labeled with high vulnerability suffer from bad connectivity.

Despite being absent from the selected set of variables, some important indicators reappear during the interpretation of the results. For example, specific occupations like the agriculture sector were omitted because of data availability issues. However, its contribution appears clearly when comparing vulnerability maps to the main activities of the concerned areas.

Conclusion

This article performed a spatial analysis of social vulnerability in the province of Chlef. The analysis, based on an empirical, place-based assessment, resulted in the mapping of the spatial variability of social vulnerability for the 35 municipalities in the province. The assessment replicated the SoVI tool with some necessary and common adaptations to become applicable to the context of the study area. The results reveal that the SoVI was able to identify the underlying factors influencing the social vulnerability of the municipalities. This demonstrates the convenience of the SoVI as a tool for decision-making regarding risk management, especially during early phases. It helps to identify the most vulnerable units, to understand the spatial variability of social vulnerability and to identify critical domains that have to be dealt with for risk management. Since the underlying factors are derived from empirical data, the relevance of the results to the context is guaranteed.

The resulting vulnerability maps match with both the human and physical geography of the province. The spatial distribution of social vulnerability at Chlef is a direct reflection of its natural features and its territorial structure. Lower social vulnerability is linked to diversified economic activity and connectivity. While high vulnerability is associated with remote regions, undiversified activity -mainly agricultural- and mountainous landscape. Those characteristics shaped the direct vulnerability factors such as housing quality, basic infrastructure, education level, wealth, housing stock, socioeconomic development and land use, which in turn influence the trend of social vulnerability level. This confirms the importance of the preliminary geographical analysis of the area targeted by the vulnerability assessment. The mapping of major physical and human elements of the territory is a useful tool for a knowledgeable interpretation of SoVI results.

Two major drawbacks of the study must be discussed. First, the data source dates back to 2008. A recent census was carried out in 2022, but its results are not yet published. Further studies have to be carried out with up-to-date data. They will allow the comparison between the two periods, as well as the study of the social vulnerability evolution and the SoVI sensitivity to time changes. The second drawback concerns the number of spatial units included in the assessment. Being a statistical method, the PCA efficiency increases with the size of the sample. The SoVI methodology recommends 100 units for better results. To respect this recommendation, in future works, the study area has to be extended to the regional level instead of the province.

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