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A Novel Approach to Measuring Spatiotemporal Changes in Social Vulnerability at the Local Level in Portugal

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Abstract Social vulnerability, as one of the risk components, partially explains the magnitude of the impacts observed after a disaster. In this study, a spatiotemporally comparable assessment of social vulnerability and its drivers was conducted in Portugal, at the civil parish level, for three census frames. The first challenging step consisted of the selection of meaningful and consistent variables over time. Data were normalized using the Adjusted Mazziotta-Pareto Index (AMPI) to obtain comparable adimensional-normalized values. A joint principal component analysis (PCA) was applied, resulting in a robust set of variables, interpretable from the point of view of their self-grouping around vulnerability drivers. A separate PCA for each census was also conducted, which proved to be useful in analyzing changes in the composition and type of drivers, although only the joint PCA allows the monitoring of spatiotemporal changes in social vulnerability scores and drivers from 1991 to 2011. A general improvement in social vulnerability was observed for Portugal. The two main drivers are the economic condition (PC1), and aging and depopulation (PC2). The remaining drivers highlighted are uprooting and internal mobility, and daily commuting. Census data proved their value in the territorial, social, and demographic characterization of the country, to support medium- and long-term disaster risk reduction measures.

1 Introduction

In this section, we provide the context of previous social vulnerability studies, highlighting the characteristics of the input data, the normalization methods, and the statistical procedure adopted. We then present the aims of our study.

1.1 Contextualizing Social Vulnerability Assessments

Despite the existence of many perspectives and concepts related to vulnerability (Maiti et al. 2017; Contreras et al. 2020; Bigi et al. 2021), in general, all point to the characteristics of individuals, communities, or other exposed elements (whether physical, social, economic, or environmental) that increase their propensity to hazard impacts (United Nations 2016). This implies that vulnerability plays a significant role in explaining the magnitude of disasters (Alexander 2012; UNDP 2017; Marulanda-Fraume et al. 2020).

This study focused on social vulnerability (SV), which is defined as the propensity of individuals, communities, and systems to be harmed by hazardous processes, based on their social and demographic characteristics and territorial context (Cutter et al. 2003; Mendes 2009; Yoon 2012; Chen et al. 2013; Tavares et al. 2018; Mendes et al. 2019; Ogie and Pradhan 2019) and their ability to cope with and recover from the negative impacts of hazardous processes (Eidsvig et al. 2014).

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In this context, SV can be captured by using several variables, due to its complexity and dynamic and multidimensional characteristics that need to be assessed taking into account the spatial and temporal trends, and by evaluating how different vulnerability dimensions change over time and space (Frigerio et al. 2018). The variables that express SV are related to its main drivers—age, economic condition, disability, education, gender, employment, housing conditions, mobility, and ethnicity—which are some of the most commonly considered in the literature (Fekete 2010; Finch et al. 2010; Yoon 2012; Bergstrand et al. 2015; Rufat et al. 2015; Cutter 2017; Contreras et al. 2020).

When dealing with the assessment, the different types of vulnerability require different representative and explicative variables available for the vulnerability assessment in a specific period. Frequently, lack of data can lead to reliance on variables that may not be the most accurate indicators of vulnerability (Zhou et al. 2014).

The scale of the assessment—global, continental, subcontinental, national, regional, provincial, municipal, or local—determines the type of data to be collected and the assessment approaches (Contreras et al. 2020). When vulnerability studies are developed at the local level, even in study areas considered as data-scarce contexts, population censuses are widely used as data sources to construct robust datasets to allow the application of factor analysis (Dintwa et al. 2019; Contreras et al. 2020). Many other data sources beside census data can be used (e.g., household level interviews), but require intense fieldwork that limits the spatial coverage of the assessment. Population census data are commonly used to define spatial units of analysis (e.g., municipality, district, block), and variables are represented as percentages of the total number of individuals, by density functions and per capita or per powers of 10 individuals (Hofflinger et al. 2019). Census data contain national data and statistics for regional, municipal, and local spatial units (civil parishes and blocks) for the same reference date and using the same data collection methodology, usually updated every 10 years. When variables represent the adaptive capacity through territorial features (e.g., public and private infrastructure and services such as hospitals, grocery stores, and so on) that reduce or mitigate impacts, it is common to use densities or distances to the considered features (Mendes et al. 2019). Household level vulnerability assessments often require observations from transect walks and sample semistructured interviews, combining quantitative and qualitative methods of data collection (Huynh and Stringer 2018). When using spatial units of analysis with a small number of residents or households, a representativeness bias may occur, justifying or suggesting their exclusion from the analysis (Apotsos 2019).

Social vulnerability assessments are commonly based on spatial indices, which require the selection of indicators, their normalization and weighting, and aggregation into an index (OECD 2008) that must represent aspects of a society's ability to prepare for, deal with, and recover from a disaster (Eidsvig et al. 2014). Variable selection is a key step of SV assessments, that is, identifying SV indicators that are suitable due to data availability and accessibility over longer periods. Selection can be conceptually biased, and concepts and interests of both scientists and decision makers may change over time, or original indicators such as unemployment may decrease in importance to explain national or regional social stress (Fekete 2019b).

The most sensitive step for constructing an index is the weighting of individual variables to construct a vulnerability index (Adger et al. 2004; Zebardast 2013). The objectives of indicator weighting are: (1) to investigate any correlation among indicators to detect overlapping information; and (2) to select a suitable weighting and aggregation approach for the final index calculation (Contreras et al. 2020).

After being weighted, indicators can be aggregated using additive, multiplicative, or decision rule models (Eidsvig et al. 2014). Each method for the spatial assessment of SV is selected according to the research aim, case study area, scale, reliability of data sources, spatial variables and indicators available, geohazard to address, the scope of the research, and the level of funding (Contreras et al. 2020).

The spatial dimension is crucial to understanding and evaluating SV drivers and adopting the adequate units of analysis and multivariate methods (Fekete 2019a), either from the perspective of scale or from the perspective of the typology of hazard. At smaller scales (for example, regional, county, or district level) SV studies are abundant (Chen et al. 2013; Guillard-Gonçalves et al. 2015; de Loyola Hummell et al. 2016; Tavares et al. 2018), and frequently devoted to a particular hazard like earthquakes (Frigerio et al. 2016), flooding (Fekete 2010; Roder et al. 2017), landslides (Guillard-Gonçalves and Zêzere 2018), and tsunamis (Barros et al. 2015).

Vulnerability assessment has been conducted and applied to disaster risk reduction strategies by researchers, practitioners, and decision makers faced with the problem of conducting reassessments that allow them to understand the temporal evolution of vulnerability. Despite a large body of literature that has proposed and discussed SV indices, there are few studies about the spatiotemporal dynamics of social vulnerability (Cutter and Finch 2008; Zhou et al. 2014; Frigerio et al. 2018; Tavares et al. 2018; Fekete 2019a; Park and Xu 2020; Bronfman et al. 2021). These studies have revealed that the explanatory factors of the higher levels of vulnerability may persist or change over time, which means that territories that used to be highly vulnerable at one time may no longer be so vulnerable, or the opposite (Bronfman et al. 2021). How different vulnerability dimensions change over time and how they can be comparable over different

temporal frames demands a challenging process of component normalization and quantification (Frigerio et al. 2018) for dynamic temporal monitoring, instead of a static social vulnerability snapshot (Fekete 2019b).

The available literature on the spatiotemporal dynamics of social vulnerability is usually focused on z-score normalization based on the spatial unit mean score by decade (Cutter and Finch 2008; Zhou et al. 2014; Fekete 2019a; Bronfman et al. 2021), or on the Adjusted Mazziotta-Pareto Index (AMPI) normalization (Frigerio et al. 2016; Frigerio et al. 2018). Fekete (2019b) normalized values of variables with z-scores and compared the temporal changes in positive and negative social vulnerability values in different spatial units, which, however, does not allow for a quantitative comparison of SV between time frames. One way out to achieve comparability between SV scores over time requires that both the minimum and maximum values are not time dependent (Mazziotta and Pareto 2021).

1.2 Aims of the Study

To address the existing gap in terms of SV comparability over time, the main purpose of this study was to suggest a methodology that would allow the spatiotemporal characterization of social vulnerability and its drivers. The approach was tested for three population and housing Censuses (1991, 2001, and 2011) in Portugal at the civil parish administrative level (smallest territorial subdivision with elected authorities) and followed four specific objectives:

(1) Test a normalization methodology that provides temporally comparable input data for SV assessment;
(2) Calculate comparable SV scores and SV drivers, using the same variables in three temporal frames, by applying a principal component analysis (PCA) to a single dataset, following the social vulnerability index (SoVI) approach (Cutter et al. 2003);
(3) Analyze the spatiotemporal changes in SV between 1991 and 2011; and
(4) Discuss the advantages and constraints of the methodology.

The research introduces a novel methodological approach by assessing SV based on a single PCA, in which the input data were normalized for multiple temporal frames (1991, 2001, and 2011). This provides both comparable SV scores as well as comparable SV drivers over time. The method can be adapted to other countries and regions.

2 Study Area

The study area is the continental part of Portugal located in southwestern Europe, with a population of 10.047 million (INE 2011) and an area of 89,046 km². The climate is Mediterranean, with an oceanic influence in the amplitude of temperature (lower amplitude in coastal than in inland regions). Climate and morpho-structural units (which summarize elevation, proximity to coastal areas, and geology) are key natural factors to explaining the spatial pattern of human settlement in Portugal. These natural characteristics explain, on a regional scale, the suitability of soils for agriculture and, inherently, the human presence, as well as the main rivers for the location of ports and cities (Fig. 1a). The most populated main cities are located at the mouth of or along the major rivers (Fig. 1b). Close to 75% of the population resides in civil parishes located below the elevation of 200 m (Fig. 1a).

At the administrative level, a civil parish is the smallest territorial subdivision with elected authorities. The most updated and available demographic information at the civil parish level dates from the 2011 population Census (INE 2011) (Figs. 1b and 1c).

Figure 2 illustrates three indicators frequently associated with SV—percentage of women participating in the labor force (Women employment, WomEmp) 2011 (Fig. 2a); percentage of single person private households with a person aged 65 years or older (Fam65), 2011 (Fig. 2b); and percentage of households without the benefit of at least one basic infrastructure (BasInfr) (Fig. 2c), for example electricity. These indicators express the strong dichotomy between the coastal areas—with better soils for agriculture, and more urbanization and industrialization—and the rural, more isolated inland regions.

Despite recent positive developments in most of these indicators, Fig. 2a shows that women's employment is still low, particularly in the inner rural and mountainous civil parishes. In terms of housing conditions, improvements are more evident: at least one basic infrastructure—electricity, sanitary facility, public water supply, or bathroom—was missing in more than 15% of the dwellings in only 68 of the 4037 civil parishes in 2011 (Fig. 2c), while in 1991 this was true for 3564 civil parishes.

At the national scale, an exodus from rural to urban areas, particularly to the Lisbon and Porto metropolitan areas occurred particularly after World War II. That pace has reduced in recent decades but migration still occurs, compounded by immigration from Brazil, Africa, and Eastern Europe. Within the inland regions, the population growth in medium and small cities has been occurring at the expense of the small villages (see Fig. 1c). The demographic dynamics have been powered by a general improvement of the population's qualifications and
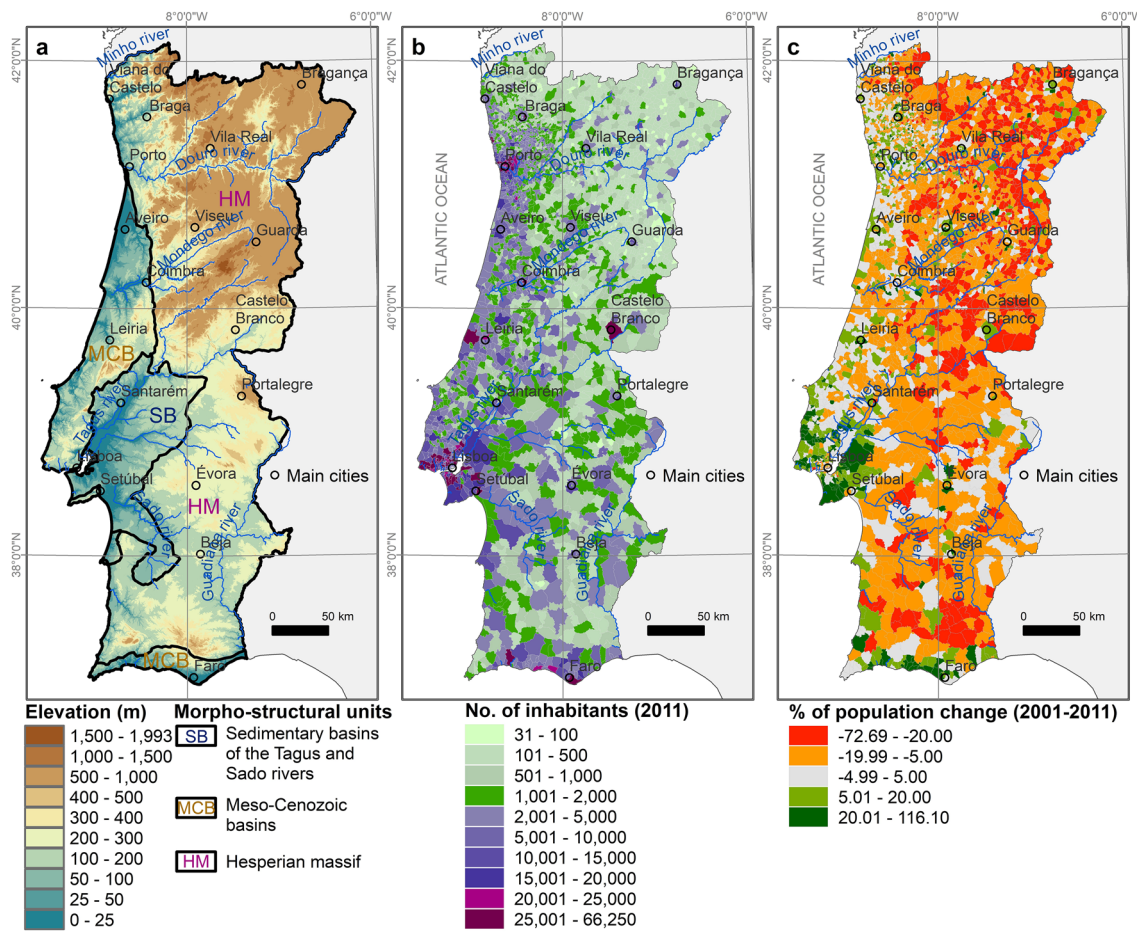
Fig. 1 Elevation and morpho-structural units (**a**), number of inhabitants in 2011 (**b**), and percentage of population change (2001–2011) (**c**) at the civil parish level in Portugal

internal mobility by individual and collective transportation, leading to the concentration of the population in urban coastal areas and an increase of the labor force in the service sector, coupled with a decrease of the working population in agriculture in recent decades. The main hazards that affect Portugal—accounting for observed and potential consequences—are coastal erosion, floods, landslides, forest fires, droughts, heatwaves, desertification, and earthquakes (DGT 2019).

3 Data and Methods

A summary of the methodological steps to assess SV in a comparable way—in three sequential time frames corresponding to the three population censuses—is illustrated in Fig. 3. The initial step of selecting the unit of analysis and the available data revealed itself as a crucial step. The feasibility of the assessment and its reliability depend on that selection. After normalizing the raw input data through the

Adjusted Mazziotta-Pareto Index (AMPI) (Mazziotta and Pareto 2016), a series of iterative steps is performed before a final SV model can be reached. The variables used in the PCA need to be clearly interpreted regarding their role in explaining SV and they need to self-aggregate in principal components (PCs) that express SV drivers in an interpretable manner.

Principal component analysis is the most common method used to assess social vulnerability (Contreras et al. 2020). In SV temporal comparisons, a PCA is usually developed for each period (census data) (Cutter and Finch 2008; Frigerio et al. 2018). The innovative contribution of the SV assessment in this study is the use of a joint PCA performed with the same spatial units and statistical variables, comparable over time, using census data of three time frames. We proposed the terms "joint PCA" or "joint analysis" to refer to this PCA performed with the same spatial units over the three time frames. The results are temporally comparable, dimensionless, and normalized SV scores, together with intermediate scores of SV drivers, for the years 1991, 2001, and 2011.
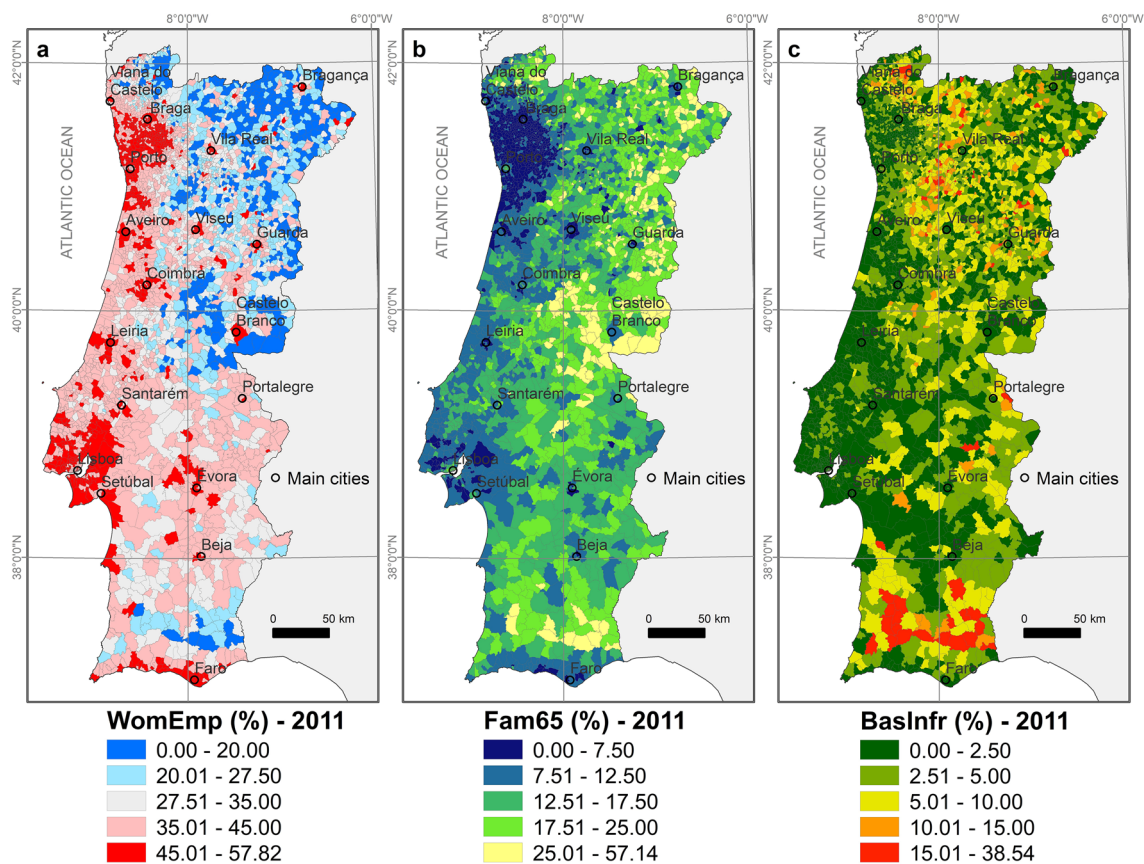
Fig. 2 Women participating in the labor force (Women employment, WomEmp) (%), 2011 (**a**), single person private households with a person aged 65 years or older (Fam65) (%), 2011 (**b**), and percentage of households without the benefit of at least one basic infrastructure, for example electricity (BasInfr) (%), 2011 (**c**) at the civil parish level in Portugal. Manual classification based on natural breaks
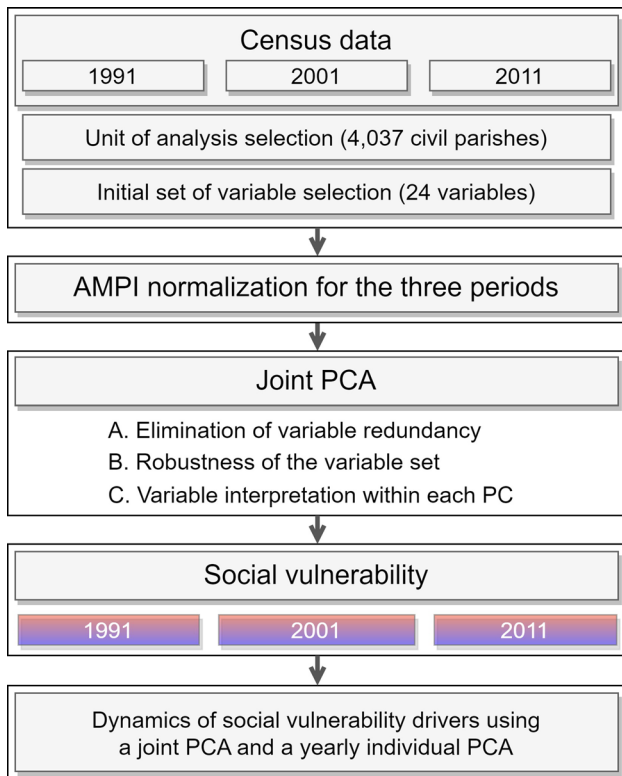
3.1 Unit of Analysis and Selection of Variables

The unit of analysis is the civil parish, the smallest administrative unit below the municipality level. Considering the administrative configuration at the time of the last available population Census (2011), a civil parish has a mean area of 22.1 km², which allows a highly detailed level of analysis. The most densely populated areas (NW quadrant of Portugal) match with the civil parishes with the smallest areas. In 1991 and 2001 there were 4037 civil parishes, whereas by 2011 that number had increased to 4050 due to an administrative revision. The adopted number of individual units for the PCA was therefore 4037 civil parishes, which implied the recalculation of variable values for 2011 based on a weighted mean using the number of residents.

In the work of Frigerio et al. (2018) in Italy, a total of 8092 spatial units was used, which corresponds to the level of the commune, an administrative unit similar to the Portuguese level of the municipality. This level of analysis was disregarded in Portugal because it would result in a coarse level of detail (278 municipalities in continental Portugal), and there are several nationwide studies already available at the municipal level (Mendes 2009; Tavares et al. 2011; Tavares et al. 2018), while studies at the civil parish level are scarce, particularly crossing several time frames. Due to these reasons, this study used the civil parish as the unit of analysis.

A more detailed level of analysis—the statistical block—would not be possible or recommended because of the lack of a spatial correspondence among intercensus statistical blocks, and the absence of an adequate number of common variables in the different population censuses.

In this research, we initially gathered data for 28 variables available at the civil parish level for the three population censuses: 12 variables characterizing housing, and 16 variables characterizing individuals and families. From these 28 variables, 4 were excluded before the PCA analysis because their interpretation in terms of SV is inconclusive or redundant when compared with other variables—number of buildings; percentage of nonconventional households (for example, military and detention facilities); number of conventional households; and number of floors per building (the

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│                  Census data                     │
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│  │ Unit of analysis selection (4,037 civil   │  │
│  │              parishes)                     │  │
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│  │ Initial set of variable selection         │  │
│  │          (24 variables)                    │  │
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│      AMPI normalization for the three periods    │
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│                  Joint PCA                       │
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│  A. Elimination of variable redundancy           │
│  B. Robustness of the variable set               │
│  C. Variable interpretation within each PC       │
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│              Social vulnerability                │
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│  Dynamics of social vulnerability drivers using  │
│  a joint PCA and a yearly individual PCA         │
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Fig. 3 Methodological flowchart for the assessment of social vulnerability (SV) that is temporally comparable (joint principal component analysis, PCA), and the analysis of SV drivers by applying a yearly individual PCA. AMPI = Adjusted Mazziotta-Pareto Index

latter has a strong correlation with the number of buildings with one household). The initial set of data based on which the PCA was first calculated included 24 variables (Table 1).

Missing values were found in three variables: WomEmp, in 1991 (59 parishes); SchLeav in 1991 and 2011 (3 and 24, respectively); and SociVal for the three censuses (249, 76, and 1, respectively for 1991, 2001, and 2011). Linear regression was used to estimate the missing values, using data from the other censuses.

The available initial set of 24 variables is representative of dimensions (see Table 1) usually considered in social vulnerability studies (Cutter et al. 2003; Chen et al. 2013; Rufat et al. 2015; Fatemi et al. 2017; Roder et al. 2017; Dintwa et al. 2019; Mendes et al. 2019). Fekete (2019a) highlighted the need for more research on the validation and justification of the variables used in the social vulnerability assessments with a scientific rationale. This is a challenge when dealing with national-level analysis at the detail scale of the civil parish.

Generally, education variables (SchLeav, Illiter, HighEdu) are reflected in better-informed decisions prior to, during, and after disasters and are also related with the socioeconomic condition. Age variables (Fam65, U14yrs, MeanAge)

are basic indicators of SV independent of the socioeconomic conditions: a child, for example, is unconditionally dependent on others in terms of mobility and nurturing. Family structure (NucChil), represented here by the percentage of couples with children, limits the ability to respond during an emergency, and after the event by limiting the work capacity and requiring care time to be shared among the family members. Type of employment (SociVal) and car usage in daily commuting (CarUsag) are linked to education and income, whereas women's participation in the labor force (WomEmp) expresses the emancipation of women and their contribution to household revenue. SociVal is a variable available at the Statistics Portugal institute, and it is a quotient between the number of employees working as specialists of intellectual and scientific activities and employees working as executive managers, directors and directors or chiefs of governance bodies, and the total number of employed persons. Gender (WomPop) is associated with lower wages and family care responsibilities. Population change (PopChan) relates to sociodemographic dynamism and territorial support capacity in terms of available infrastructure and services to foster response, recovery, and employment opportunities. Work or study place and travel time (OtheMuni, Commut) reflect the potential constraints after major disasters and a higher financial effort in maintaining or reestablishing daily routines. Internal mobility (5yrMuni) and migrant population (Foreign) express uprooting, less familiarity with local assets, less support from family members, and potential language and cultural barriers.

Building age and time of construction (BuilAge, Buil10y) reflect the housing conditions (healthiness, seismic resistance, access by wheelchair, gas installation, and so on). The lack of one or more basic infrastructure elements in the dwelling (BasInfr)—electricity, sanitary facility, public water supply, or bathroom—and overcrowded living quarters (OverCro)—an indicator of the number of rooms over or under the number of residents—are indicators of economic disadvantage and high vulnerability. The ownership of dwellings (Owners, Renters) expresses indirectly the economic condition of residents. Owning and renting a house poses distinct and quite often unclear interpretations of the implicit financial effort. In general, renters represent lower economic capacity and are more prone to eviction. The seasonality of dwelling usage (Season) and the typology of the building, that is the percentage of buildings with one dwelling (Buil1dw), are typical of rural areas and, according to several authors, rural residents are generally more vulnerable and have less access to services and infrastructure that mitigate impacts and promote a better recovery from disasters (Cutter et al. 2003; Mendes et al. 2019).

Table 1 Vulnerability dimensions and variables available in the Portuguese Census of 1991, 2001, and 2011 at the civil parish level

Vulnerability dimension	Variable code	Variable description	Related to
Educational level	SchLeav	School leaver rate (%)[a]	Individuals
	Illiter	Illiteracy rate (%)[b]	Individuals
	HighEdu	Proportion of resident population with higher education completed (%)	Individuals
Migrant population	Foreign	Proportion of resident population of foreign nationality (%)	Individuals
Internal mobility	5yrMuni	Proportion of resident population who 5 years before lived outside the municipality (%)	Individuals
Daily commuting	Commut	Average time spent on commuting (min) by the employed or student resident population	Individuals
	OtheMuni	Proportion of resident population who works or studies in another municipality (%)	Individuals
Age	U14yrs	Proportion of resident population 14 years old or younger (%)	Individuals
	MeanAge	Mean age (years) of resident population	Individuals
	Fam65	Proportion of single person private households with a person aged 65 years old or older (%)	Individuals
Gender	WomPop	Proportion of female resident population (%)	Individuals
Demographic dynamism	PopChan	Variation ratio of resident population between census years (for example, 2001–2011) (%)[c]	Individuals
Family structure	NucChil	Proportion of family nuclei of couples with children (%)	Individuals
Socioeconomic status	SociVal	Proportion of professionals socially more valued (%)	Individuals
	WomEmp	Women's employment rate (%)[d]	Individuals
	CarUsag	Proportion of car usage on daily journeys (%)	Individuals
Living/building conditions	BuilAge	Mean age of buildings (years)	Dwelling
	Buil10y	Proportion of buildings constructed in the last 10 years (%)	Dwelling
	Owners	Proportion of conventional dwellings occupied by the owner (%)	Dwelling
	Renters	Proportion of rented or subrented conventional dwellings (%)	Dwelling
	Season	Proportion of conventional dwellings with seasonal use (%)	Dwelling
	BasInfr	Proportion of conventional dwellings without at least one basic infrastructure (%)	Dwelling
	OverCro	Proportion of overcrowded living quarters (%)	Dwelling
	Buil1dw	Proportion of buildings with one dwelling (%)	Dwelling

[a](Resident population aged between 10 and 15 years old who left school without attaining lower secondary education / Resident population aged between 10 and 15 years old) × 100

[b](Resident population 10 years and older who does not know how to read or write / Resident population 10 years and older) × 100

[c]Example for the variation between 2001 and 2011: [(Resident population 2011−Resident population 2001) / Resident population 2001] × 100

[d](Female employed population / Female resident population) × 100

3.2 Normalization of Input Data

The normalization method used is based on the Adjusted Mazziotta-Pareto Index (AMPI) (Mazziotta and Pareto 2016; Frigerio et al. 2018). The AMPI allows for the comparison of values of variables from distinct time frames, assuming a reference value of 100. After assembling the input data for the 24 initial variables, for the years 1991, 2001, and 2011, four steps were conducted to obtain the normalized values:

(1) Relate value x of civil parish i with the mean, for the three temporal frames t_n (Eq. 1):

$$D_{i,t_n} = \frac{x_{i,n}}{\overline{x}_n} \times 100 \tag{1}$$

where D_{i,t_n} is the relation, or "distance", of x_i to the mean, multiplied by 100.

(2) Calculate half of the range of D_{i,t_n} considering the values of all three temporal frames t_1, t_2, and t_3 (1991, 2001, and 2011, respectively) (Eq. 2):

$$\Delta = \frac{max_{D_{i,t1:t3}} - min_{D_{i,t1:t3}}}{2} \tag{2}$$

where Δ is a constant value for the three temporal frames t_n, a unique value in each variable.

(3) Calculate the goalposts of the normalized values (Min_g and Max_g) by summing and subtracting 100 to Δ:

$$Min_g = 100 - \Delta \tag{3}$$

$$Max_g = 100 + \Delta \tag{4}$$

where Min_g and Max_g are constant values for all the i civil parishes in all the t_n temporal frames.

(4) Finally, the normalized value r_{i,t_n} to be used in the PCA is calculated as:

$$r_{i,t_n} = \frac{D_{i,t_n} - Min_g}{Max_g - Min_g} \times 60{-}70 \qquad (5)$$

All four steps were applied to each of the 24 considered variables. By applying this sequence of steps, a normalized series is obtained, where the mean of the series t_1 (1991) is the baseline value of 100.

3.3 Calculation of Social Vulnerability

After data collection, data integration to the adequate unit of representation (a percentage in most of the variables), and data normalization, SV scores are calculated using the SPSS$^{©}$ software.

3.3.1 Statistical Procedure

The SV score calculation procedure is as follows (also see Fig. 3):

(1) Testing of multicollinearity between variables by analyzing the Pearson correlation matrix and deciding which variable to keep based on three criteria: avoid communalities < 0.5; aim for a Kaiser-Mayer-Olkin (KMO) measure > 0.7; and a percentage of variance explained > 60%.

(2) Performing principal component analysis (PCA) using Varimax rotation.

(3) Extracting and interpreting the principal components (PCs) with Eigenvalue > 1. The interpretation is based on the coherence (in terms of SV interpretation) of the cardinality assigned to the variables self-grouped around the same PC.

(4) Evaluating the need to invert the PC scores. According to the cardinalities of the most explicative variables in each PC (those with loading >|0.5|, although in some cases, the loadings in the range |0.4| were also considered). In some cases, it was necessary to multiply the PC scores by –1, in order to make high scores represent high SV in such a PC, whereas low scores represent low SV.

(5) Summing the PC scores weighted by the percentage of explained variance in order to obtain a final score of SV.

Two additional notes are necessary in detailing the above steps. The analysis of communalities mentioned in step 1

was revealed as a relevant criterion. The communality (h^2) is a decision criterion used to include or exclude a variable from PCA. It is defined as the sum of the squared factor loadings of a given variable and measures the proportion of each variable's variance that can be explained by the factors. To say that a given variable has an $h^2 = 0.9$, for example, means that if we predict the value of that variable from the PCs, we would find a coefficient of determination (r^2) of 0.9. In the SV assessment, variables with communalities under 0.5 do not contribute significantly to explaining the underlying drivers of social vulnerability.

The second note regards step 5 and concerns the use of weights on the PC scores before their summation. In several studies, weights are not applied. The SoVI itself (Cutter et al. 2003) was applied elsewhere in both ways. Finally, classification of both SV and its PC scores is made according to the standard deviation (SD), which is valid for the considered time frames.

3.3.2 Joint Principal Component Analysis (PCA) and Yearly Individual PCA

As summarized above, SV scores were calculated for each civil parish, for the years 1991, 2001, and 2011, following two approaches:

- First, a single PCA using the 12,111 individuals (three temporal frames times 4037 parishes) was applied initially with the 24 variables, reaching a final model with 15 variables. This approach is defined as the joint PCA.
- The other approach uses the same 15 variables obtained in the joint PCA assessment, but applies three separated PCAs, one for each census year. This approach is defined as the yearly individual PCA.

Our purpose was to complement the joint PCA analysis in terms of the analysis of SV drivers (that is, each principal component), and the role of each variable within each driver. The purpose was not to obtain alternative scores of SV, as they are not comparable (not even for the year 1991) because the mean of SV, and each SV driver, in the yearly individual PCA always equals 0.

4 Results and Discussion

This section is structured as follows: (1) analysis of the input data is performed, focusing on the effect of the AMPI normalization over the cardinality of variables considering their role in SV; and (2) the results obtained from the joint PCA SV assessment are presented in terms of the spatiotemporal dynamics and the drivers of SV.

4.1 Characteristics of the Input Data Under the Social Vulnerability Perspective

A significant and often unrecognized limitation of using census data in SV assessments is that the census data reduce the complexity of the assessment because most census data are only proxy indicators of the propensity to be harmed by hazardous processes. The use of census data, however, is reasonable due to data availability and consistency over large regions and time frames. Table 2 analyzes the Pearson correlation between the original raw values of the input data (normally expressed as%) and their AMPI-normalized, nondimensional, values. Based on that result (+1 or –1), the concordance between this later value used in PCA and its role in describing SV is evaluated. The majority of variables presents a concordance—that is, the higher the variables' value the higher SV. Exceptions are, for example, the variables percentage of residents with higher education (HighEdu), percentage of working population that uses a car on daily journeys (CarUsag), and

Table 2 Correlation coefficients between the raw values of variables and their Adjusted Mazziotta-Pareto Index (AMPI)-normalized scores for principal component analysis (PCA), and interpretation of the concordance of the AMPI-normalized scores with their role in interpreting social vulnerability

Vulnerability Dimension	Variable Code	Pearson Correlation[a]	Are the AMPI-Normalized Scores for PCA Concordant with Their Theoretical Role in Interpreting SV?
Educational level	SchLeav	1	Yes. The higher the school leavers rate the higher SV.
	Illiter	1	Yes. The higher the illiteracy rate the higher SV.
	HighEdu	1	No. The higher the% of residents with higher education the lower SV.
Migrant population	Foreign	1	Yes. The higher the% of foreign residents the higher SV.
Internal mobility	5yrMuni	1	Yes. The lower the acquaintance with the residence place, the higher SV.
Daily commuting	Commut	1	Yes. The longer the commuting time the higher SV.
	OtheMuni	1	Yes. The higher the% of residents moving daily to study or work in another municipality, the higher SV.
Age	U14yrs	1	Yes. The higher the% of residents 14 years old or younger, the higher SV.
	MeanAge	1	Yes. The higher the ageing of residents, the higher SV.
	Fam65	1	Yes. The higher the% of dwellings with a single-person 65 years old or older, the higher SV.
Gender	WomPop	1	Yes. The higher the% of female population, the higher SV.
Demographic dynamism	PopChan	–1[b]	Yes. Despite the negative correlation, a loss of population is represented by higher AMPI-normalized values, which means the cardinality agrees with the assumption that less demographically dynamic areas are more vulnerable.
Family structure	NucChil	1	Yes. The higher the% of families with dependents, for example children, the higher SV.
Socioeconomic status	SociVal	1	No. The higher the% of professionals socially more valued, the lower SV.
	WomEmp	1	No. The higher the female employment rate, the lower SV.
	CarUsag	1	No. The higher the% of residents who use their own car in daily journeys, the lower SV. It is a proxy for the family economic condition as well.
Living/building conditions	BuilAge	1	Yes. The higher the mean age of buildings, the higher SV.
	Buil10y	1	No. The higher the% of recent buildings, the lower SV.
	Owners	1	No. The higher the% of dwellings occupied by the owner, the lower SV.
	Renters	1	Yes. The higher the% of rented or subrented dwellings, the higher SV.
	Season	1	Inconclusive. The higher the% of dwellings with seasonal use the lower the coverage by essential infrastructure and/or the more disfunctional the urbanization process would be, meaning eventually higher SV.
	BasInfr	1	Yes. The higher the% of dwellings without at least one basic infrastructure, the higher SV.
	OverCro	1	Yes. The higher the% of overcrowded living quarters, the higher SV.
	Buil1dw	1	Inconclusive. High% of buildings with one dwelling may represent rural areas where support capability is low, and illegal settlements, as well as medium- and high-class neighborhoods.

[a]Pearson correlation between the original raw values and the AMPI-normalized values.

[b]Negative variations in population (decreases from one census to the next) are represented in the AMPI-normalized values with the highest values (> 100).

percentage of buildings constructed in the last 10 years (Build10y). It is not relevant to assign a priori judgements on the role of the variables prior to applying the PCA. That interpretation is reserved for the step where the PCA rotated component matrix is analyzed.

The population change indicator (PopChan) was the one in which, surprisingly, the raw values were inverted by applying the normalization method. In opposition to the other variables, this was the only one that assumed positive and negative values (population gains and losses), an effect that must be acknowledged in future applications.

The iterative application of the steps described in Sect. 3.3 implied that from the initial set of 24 variables only 15 were effectively used in the final SV model. This number of variables respects the minimum individuals/variables' ratio of 5:1 usually considered. The observed ratio of 504.6 and 807.4, respectively, is considered very good (Comfrey and Lee 1992).

4.2 Social Vulnerability Using a Joint PCA

The purpose of conducting a joint analysis of SV—considering the AMPI-normalized values in 1991, 2001, and 2011—was to evaluate the social vulnerability changes over

time and compare the results between time frames. The SV joint analysis presents a minimum score of SV of –1.76 and a maximum of 2.84, a mean SV of 0 and a standard deviation of 0.57. The same SV class intervals were applied to the three census frames considering five classes: very low, < –1.5 SD (–1.76 to –0.86); low, from –1.5 SD to –0.5 SD (–0.86 to –0.29); moderate, from –0.5 SD to +0.5 SD (–0.29 to +0.29); high, from +0.5 SD to +1.5 SD (+0.29 to +0.86); and very high, ≥ +1.5 SD (+0.86 to 2.84).

4.2.1 Spatiotemporal Dynamics

Mapping the comparable scores of SV in 1991, 2001, and 2011 (Fig. 4) shows a general reduction of social vulnerability over time. In 1991 low and very low SV was only found in 293 civil parishes (7.26% of the total), most of them corresponding to the main cities (the district capitals) and to some industrialized areas around Leiria, Aveiro, and Braga, and some service areas with multiple functions such as Coimbra and Viseu. These two classes of low and very low SV had increased to 1365 civil parishes by 2001, and 2276 by 2011 (33.81% and 56.38% of the total, respectively).

Arguably, a decade interval between censuses is able to capture the long-term underlying factors of vulnerability, highlighting the relevance of applying normalization
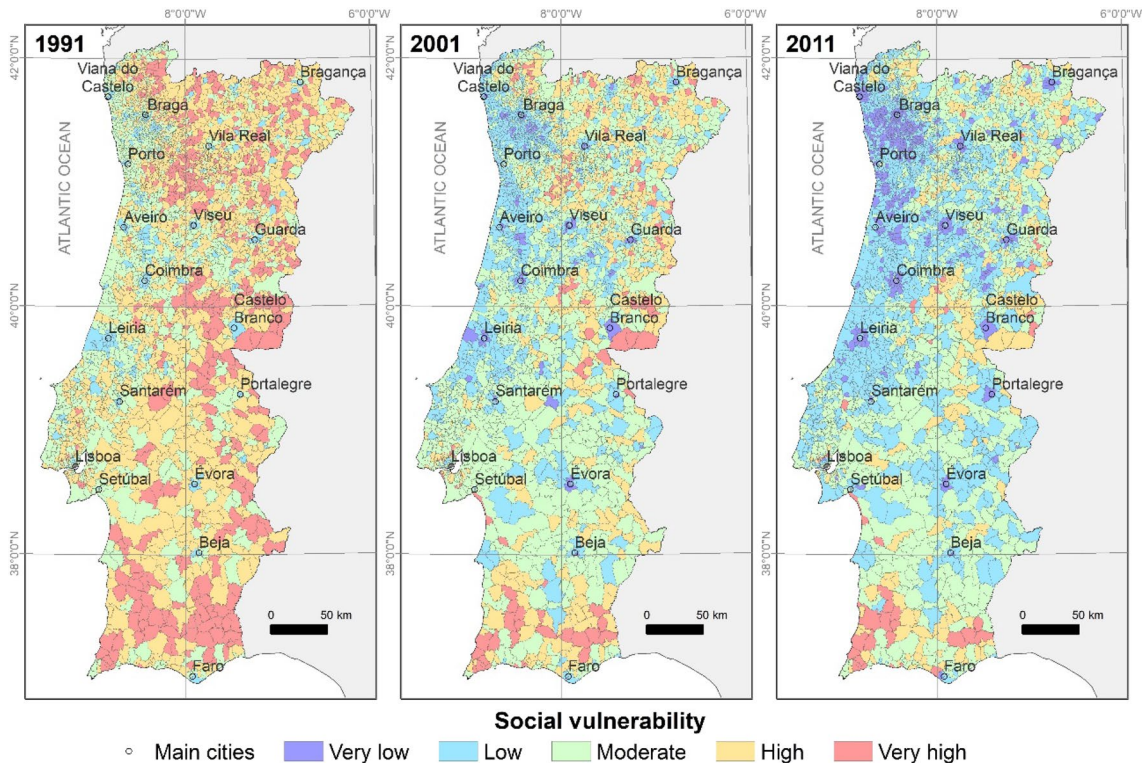
Fig. 4 Social vulnerability in 1991, 2001, and 2011 at the civil parish level in Portugal based on a single principal component analysis (PCA) performed for the three censuses. Classification using the standard deviation (SD) as explained in the text

Table 3 Changes in social vulnerability (SV) classes from 1991 to 2001, 2001 to 2011, and 1991 to 2011 at the civil parish level in Portugal, identifying the improving (green) and worsening (red) number of civil parishes

	SV class	**2001**					
		Very low	Low	Moderate	High	Very high	Total
1991	Very low	0	0	0	0	0	0
	Low	104	182	6	1	0	293
	Moderate	35	846	461	53	5	1,400
	High	2	185	1,087	391	46	1,711
	Very high	0	11	183	330	109	633
	Total	141	1,224	1,737	775	160	4,037

	SV class	**2011**					
		Very low	Low	Moderate	High	Very high	Total
2001	Very low	133	7	1	0	0	141
	Low	452	742	29	1	0	1,224
	Moderate	28	837	802	68	2	1,737
	High	0	68	452	230	25	775
	Very high	0	9	38	79	34	160
	Total	613	1,663	1,322	378	61	4,037

	SV class	**2011**					
		Very low	Low	Moderate	High	Very high	Total
1991	Very low	0	0	0	0	0	0
	Low	189	100	4	0	0	293
	Moderate	359	804	202	30	5	1,400
	High	62	685	800	142	22	1,711
	Very high	3	74	316	206	34	633
	Total	613	1,663	1,322	378	61	4,037

methods that represent such dynamics, instead of capturing just limited and static snapshots of SV in specific time frames (Fekete 2019b).

Despite the generalized improving trend of SV over time, the obtained results highlight the negative SV changes and the permanency of high and very high SV observed in some civil parishes from 1991 to 2011 (Table 3, Fig. 5): 34 civil parishes maintained very high SV, mostly located in the southern region, in the inland rural regions near Coimbra, Castelo Branco, and Guarda, and in the northern inland; 30 civil parishes changed from moderate to high and 5 to very high SV.

Table 3 also shows that from 1991 to 2001, 111 civil parishes saw their SV scores increase (figures in red), while that number rose to 133 from 2001 to 2011. Considering that in the 1991–2011 period, SV worsened in only 61 civil

parishes, it is concluded that social vulnerability is not a deterministic and immutable condition, and that in the time span of one decade significant changes can occur. In the 1991–2001 period 2783 civil parishes improved their SV classification, while in the 2001–2011 period that number was 1963.

As for the drivers of SV, after the iterative application of steps 1–3 described in Sect. 3.3, a final set of AMPI-normalized values of 15 variables was obtained that self-aggregated around four principal components (PCs), which feature a KMO of 0.815 and 73.1% of variance explained. The PCs represent the drivers of SV. The most relevant principal component (PC1) is represented by the economic condition (Table 4).

According to the cardinality of its explicative variables, the scores of PC1 were multiplied by (–1) so higher scores
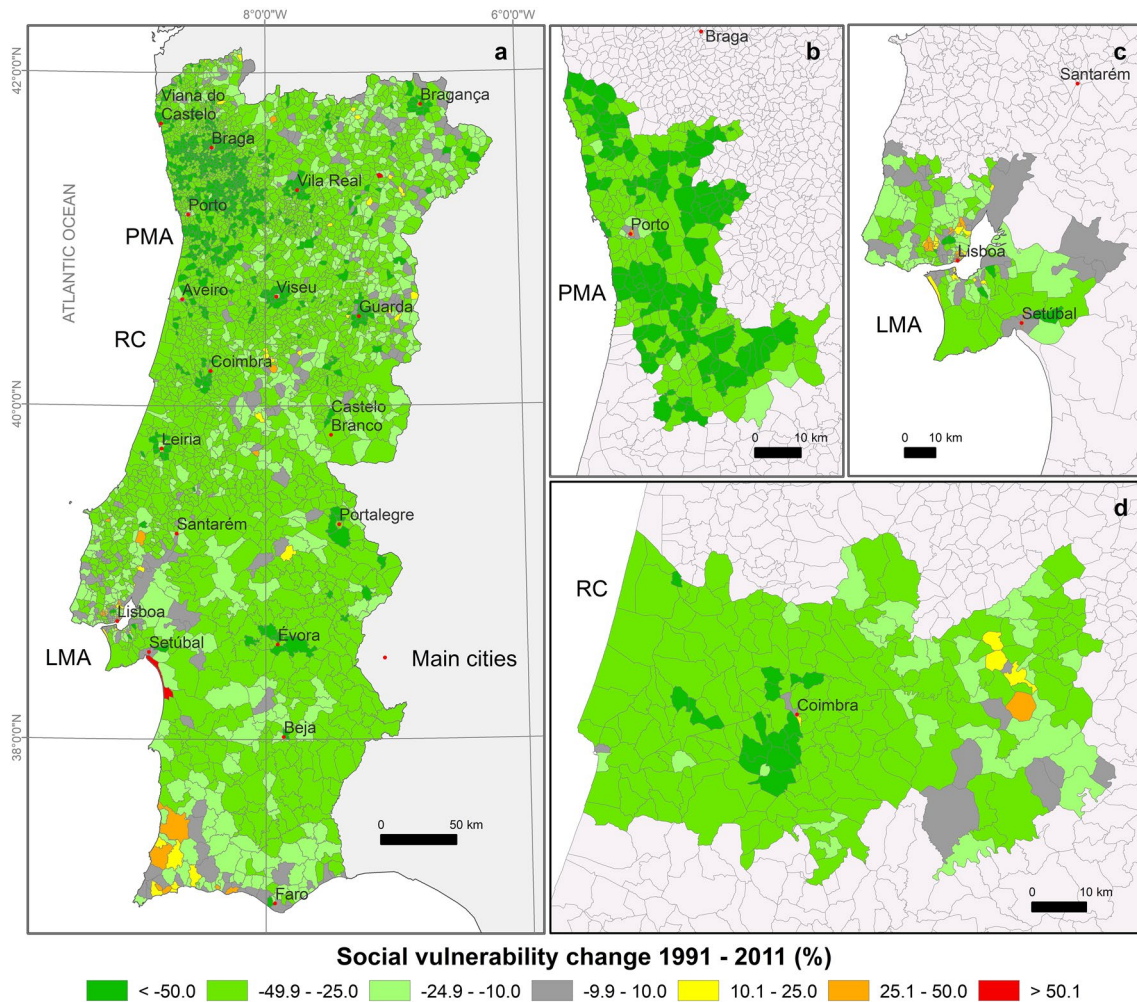
Fig. 5 Social vulnerability changes (in%) between 1991 and 2011 for Portugal (**a**), the Porto Metropolitan Area, PMA (**b**), the Lisbon Metropolitan Area, LMA (**c**), and the Region of Coimbra, RC (**d**)

may represent high SV. This was decided after verifying that, for example, a positive loading is found in the CarUsag variable and a negative loading is found in the BasInfr variable and SchLeav variable (PCA is "blind" regarding the role of each variable in explaining SV). The PC2 characterizes the population changes and population ageing as its more explicative variables are related to single-elderly dwellings (Fam65), mean age, illiteracy rate usually correlated with elder persons, and population change 2001–2011, all with positive loading. With negative loading in this PC is the variable representing women employment, a proxy of demographic dynamism and the opposite of depopulation processes. The PC3 expresses the uprooting and internal mobility of the resident population, and PC4 expresses the daily commuting and working and studying population.

4.2.2 Drivers of Social Vulnerability

This subsection presents and analyzes the results from the SV drivers (interpreted from the PCs) performed with the joint PCA. When SV scores are queried by time frame, a generalized improvement is observed from 1991 to 2011 (Table 5, Fig. 4), with the mean SV reducing from 0.392 to –0.338. However, this reduction has not occurred with regard to all the social vulnerability drivers. The less explicative PCs and, therefore, the less relevant in expressing SV (PC2 to PC4), register slight increases, countered by a significant reduction in PC1 (economic condition). The increase or the near-stagnation of the social vulnerability index in a significant number of civil parishes is mainly explained by the phenomenon of ageing and population loss in old city centers and rural areas, expressed in the scores of PC2 (see Table 4).

Table 4 Interpretation of social vulnerability (SV) drivers from the extracted principal components and their respective explicative variables

| SV Principal Component (Cardinality)	% of Variance Explained	Explicative Variables with Loading > |0.6|
PC1—Economic condition (−)	32.955	Proportion of car usage on daily journeys (%)—CarUsag (0.876)
		Proportion of dwellings without at least one basic infrastructure (%)—BasInfr (−0.829)
		School leavers rate (%)—SchLeav (−0.792)
		Proportion of overcrowded living quarters (%)—OverCro (−0.706)
		Proportion of professionals socially more valued (%)—SociVal (0.681)
		Proportion of resident population with higher education completed (%)—HighEdu (0.599)
PC2—Age and depopulation (+)	22.444	Proportion of one-person private dwellings with 65 years old or older (%)—Fam65 (0.897)
		Mean age (years) of resident population—MeanAge (0.877)
		Women employment rate (%)—WomEmp (−0.731)
		Variation ratio of resident population (e.g. 2001–2011) (%)—PopChan (0.717)
		Illiteracy rate (%)—Illiter (0.662)
PC3—Uprooting and internal mobility (+)	9.363	Proportion of resident population of foreign nationality—Foreign (0.829)
		Proportion of resident population that 5 years before lived outside the municipality (%)—5yrMuni (0.766)
PC4—Daily commuting (+)	8.340	Average time spent on commuting (min) of the employed or student resident population—Commut (0.869)
		Proportion of resident population that works or studies in another municipality (%)—OtheMuni (0.786)

Table 5 Central tendency of changes in the social vulnerability (SV) scores for each principal component

SV Principal Component	Mean Score		
	1991	2001	2011
PC1—Economic condition	1.077	−0.150	−0.927
PC2—Age and depopulation	−0.177	0.023	0.153
PC3—Uprooting and internal mobility	−0.087	−0.075	0.162
PC4—Daily commuting	−0.252	0.147	0.105
Social vulnerability	0.392	−0.053	−0.338

This bidirectional dynamic in PCs is interesting as it raises the question whether some SV drivers as expressed by PCs are more relevant than others. Are those related to employment, housing conditions, and economic conditions (expressed in PC1) more relevant than those related to uprooting, mobility, age, and demographic changes (expressed in PC2, PC3, and PC4)? Ultimately, a given parish may present a globally low SV score, but a high score in a particular PC, identifying the driver of its SV that needs to be further addressed by public policies. Analyzing each PC score individually provides an understanding of the local drivers of social vulnerability (Fig. 6). It may be found, for example, that ageing is the only driver in which certain civil parishes present high scores, requiring a dedicated intervention of public policies and the private sector in preparing and preventing greater losses from future disaster events. Figure 6 shows that PC1, economic condition, represents

the SV driver that most improved over time. Ageing and depopulation (PC2) have worsened, particularly in the inner rural areas, while uprooting and internal mobility are SV drivers more present in the metropolitan area of Lisbon and in the southern region, where tourism in the summer months represents a highly volatile economic activity that attracts nationals and immigrants.

Figure 7 supports the image provided by the mapping of SV drivers. The most weighted principal component (PC1), which explains the majority of the total variance and is related to the economic condition of residents, sustains a solid reduction of SV, despite the persistence of high scores, mainly in PC3, in an increasing number of civil parish outliers (see Fig. 6). The country changed significantly within the time span of the study. In 1991, Portugal had been part of the European Union for five years, and 17 years before the country had still been under a dictatorial regime. The behavior of the PC3 scores—uprooting and internal mobility—explained by variables related to immigration and long-term internal mobility, also highlights the cultural, social, urban, and territorial changes the country has undergone in this period, reflected by the increase in the distance among outliers and between them and the PC3 median scores, from 1991 to 2011.
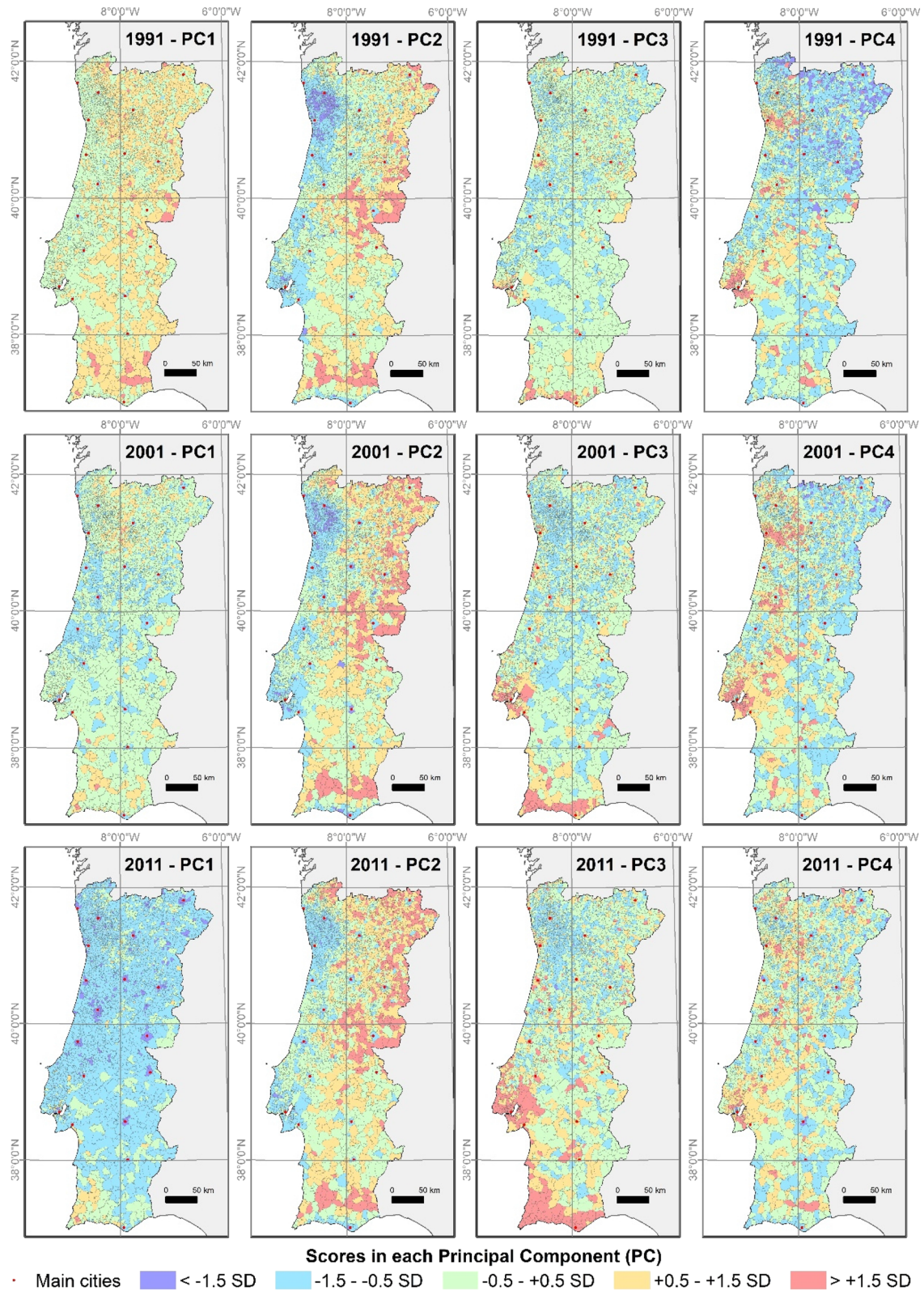
Fig. 6 Spatiotemporal changes in social vulnerability drivers between 1991 and 2011 at the civil parish level in Portugal, using a joint principal component analysis (PCA). PC1—Economic condi-tion, PC2—Age and depopulation, PC3—Uprooting and internal mobility, PC4—Daily commuting

Fig. 7 Temporal changes in social vulnerability drivers between 1991 and 2011 at the civil parish level in Portugal, using a joint principal component analysis (PCA). Circles identify outlier civil parishes with scores > 1.5 × IQR, where IQR means interquartile range, calculated as: IQR = Q75–Q25
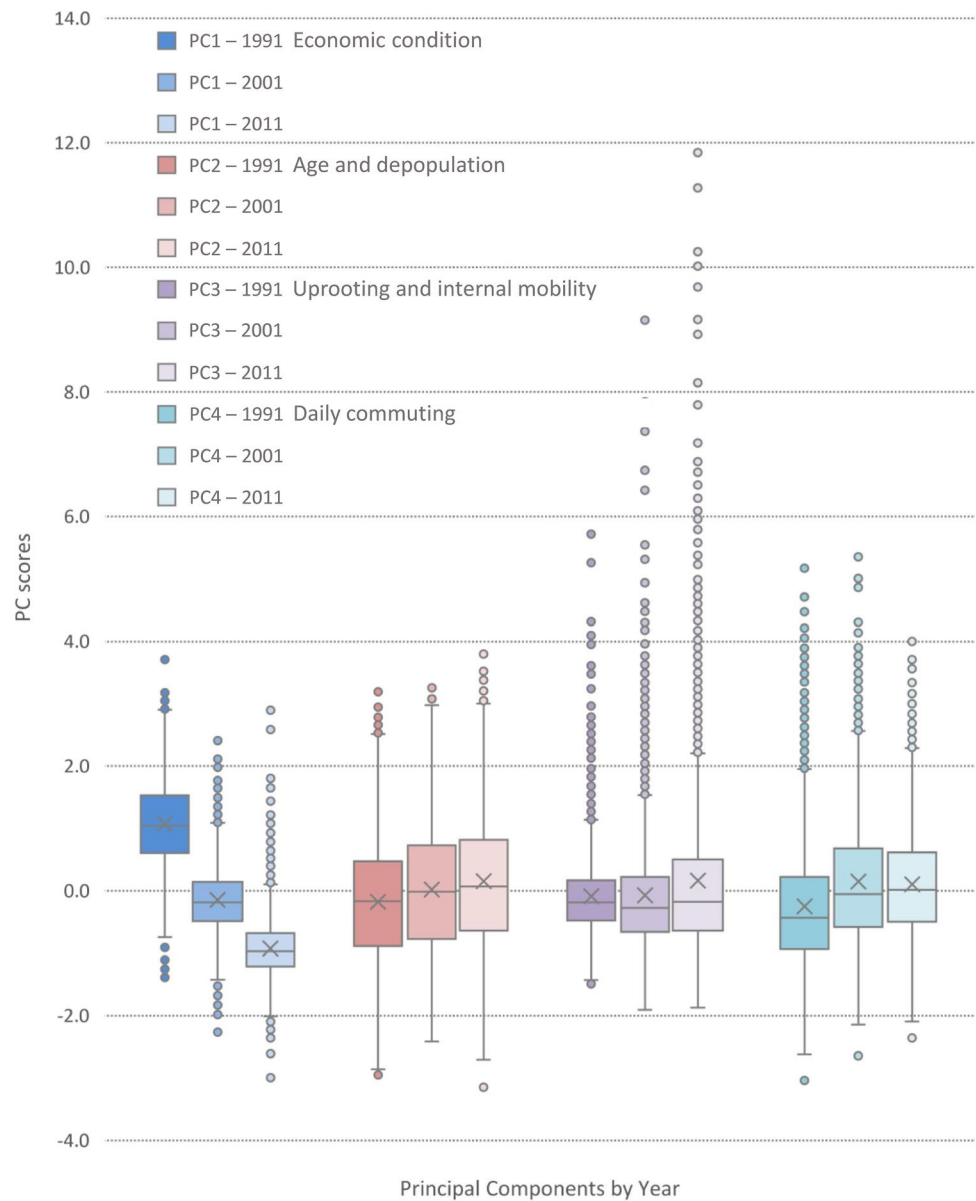
5 Additional Methodological Considerations

In this section, some additional discussion is provided about the normalization method and the complementary of using joint and yearly individual PCA.

5.1 On the Normalization Method

Standardization (for example, z-scores) is one of the most commonly used methods in SV assessments. But it only allows for relative comparisons, as those run on the values of the distinct variables of the reference time. Applying standardization to a time series comes with the drawback that every new observation will change both its mean and variance. Moreover, comparing the standardized data is a complex task as a time-series mean is challenging to understand (Mazziotta and Pareto 2018).

Intrinsically, normalization methods such as rescaling, for example, fuzzy logic (usually used by GIS modelers) or Min-Max (usually used by sociologists) becomes an alternative. However, in order to carry out assessments these require that both the minimum and maximum values are not time dependent (Mazziotta and Pareto 2021). In addition, when data are normalized with such methods, that is not done with respect to a reference point like the mean (Mazziotta and Pareto 2021). In practice this means that, for example, despite 0.5 being half of normalized values (normally ranging between 0 and 1) one cannot

easily say whether the unnormalized value of 0.6 is above or below the mean.

To overcome these constraints, we used the AMPI, which is a partially compensatory (or noncompensatory) composite index. It allows for data comparison over space and time (Mazziotta and Pareto 2016). Moreover, when PCA is performed with AMPI-normalized data, an aggregation of variables is performed that symbolizes the diverse components of the multidimensional phenomenon being analyzed (for example, social vulnerability).

5.2 On the Complementary Use of Joint and Yearly Independent Principal Component Analysis

There are some advantages and constraints when using a single joint PCA for the three censuses over the use of yearly individual PCAs. The comparison of SV scores over time in this study was made by using a single dataset for the three temporal frames. The applied methodology has the advantage of avoiding that the mean of the PC scores in each time frame equals 0, thus allowing the intercensus comparison of results. When yearly individual PCAs are conducted the mean score in 1991, 2001, and 2011, in each PC always equaled 0, which avoids an intercensus comparison.

Analyzing the communalities obtained from the two approaches—a joint PCA with 12,111 civil parishes, and three individual PCAs with 4037 civil parishes each—provides a picture of the strength of each variable within the entire dataset (Table 6). Communalities calculated from the two approaches reveal the relevance of age-related and economic-related indicators as those with high communalities (Table 6).

Over time, some variables do not contribute to the interpretation of SV as they used to—including percentage of dwellings without at least one basic infrastructure (BasInfr) and school leavers rate (SchLeav). These two variables showed a significant improvement between 1991 and 2011, accentuating their positive skewness. But the extracted communality of the variable women employment rate (WomEmp) increased from 0.443 in 1991 to 0.816 in 2011 (see Table 6), despite a modest increase of this indicator over time, which leads one to suppose the variable increased its relevance within the remaining variables.

The matrix of the rotated components of the yearly individual PCA (Table 7) confirms the age-related variables as the most relevant ones (compared with the communalities in Table 6) also in the joint analysis (compared with PC2 in Table 4). They are present in PC1 and explain most of the variance in all the census years, while in the joint PCA they explain less of the total variance. The socioeconomically related PC in the joint PCA is PC1, while in the separated analyses, its explicative variables are split between PC2 and PC3 in the 2001 and 2011 Census. The uprooting

Table 6 Communalities (h^2) between the joint principal component analysis (PCA) for the assessment of social vulnerability (SV) (12,111 civil parishes) and the yearly individual PCAs (4037 civil parishes in each of the time frames 1991, 2001, and 2011)

PC in Which the Variable Has the Highest Loading in the Joint PCA	Variable	Joint PCA h^2	1991 PCA h^2	2001 PCA h^2	2011 PCA h^2
PC2 – Age and depopulation	MeanAge	0.905	0.864	0.904	0.914
PC2 – Age and depopulation	Fam65	0.824	0.773	0.820	0.834
PC1 – Economic condition	CarUsag	0.790	0.594	0.548	0.554
PC4 – Daily commuting	Commut	0.760	0.718	0.690	0.648
PC2 – Age and depopulation	Illiter	0.744	0.716	0.747	0.730
PC4 – Daily commuting	OtheMuni	0.742	0.750	0.770	0.779
PC1 – Economic condition	BasInfr	0.739	0.620	0.357	0.464
PC1 – Economic condition	OverCro	0.737	0.674	0.735	0.782
PC1 – Economic condition	HighEdu	0.723	0.647	0.774	0.772
PC1 – Economic condition	SociVal	0.720	0.688	0.737	0.670
PC3 – Uprooting and internal mobility	Foreign	0.693	0.785	0.547	0.601
PC1 – Economic condition	SchLeav	0.676	0.595	0.455	0.134
PC3 – Uprooting and internal mobility	5yrMuni	0.666	0.669	0.570	0.643
PC2 – Age and depopulation	WomEmp	0.657	0.443	0.666	0.816
PC2 – Age and depopulation	PopChan	0.590	0.527	0.589	0.625

Stronger communalities (those ≥ 0.6) in blue scale; weaker communalities (those < 0.6) in orange scale

Table 7 Rotated components matrices for the yearly individual principal component analysis (PCA) of social vulnerability, one for each census year, using the same 15 explicative variables

	1991					2001					2011			
Variable	PC1	PC2	PC3	PC4	Variable	PC1	PC2	PC3	PC4	Variable	PC1	PC2	PC3	PC4
MeanAge	0.92	0.04	-0.10	0.06	MeanAge	0.94	0.03	-0.10	-0.12	MeanAge	0.95	0.01	-0.09	-0.03
Fam65	0.86	-0.13	-0.12	0.07	Fam65	0.90	-0.01	-0.01	-0.09	Fam65	0.91	0.04	0.03	-0.02
Illiter	0.71	-0.45	-0.11	-0.04	Illiter	0.79	-0.28	0.21	-0.06	WomEmp	-0.86	0.25	-0.11	-0.04
OverCro	-0.67	-0.45	0.13	0.00	WomEmp	-0.75	0.29	-0.16	0.01	Illiter	0.80	-0.25	0.17	0.01
PopChan	0.65	-0.21	-0.22	-0.14	PopChan	0.68	-0.25	0.23	-0.10	PopChan	0.69	-0.35	0.14	-0.06
WomEmp	-0.64	0.14	-0.08	0.11	HighEdu	-0.28	0.81	-0.20	-0.07	HighEdu	-0.39	0.76	-0.19	-0.08
SociVal	-0.15	0.77	-0.09	0.26	SociVal	-0.21	0.78	-0.23	-0.16	SociVal	-0.16	0.76	-0.22	-0.17
CarUsag	-0.11	0.76	0.07	0.04	Foreign	-0.02	0.70	0.15	0.19	5yrMuni	0.03	0.75	0.03	0.29
HighEdu	-0.19	0.73	0.01	0.29	5yrMuni	-0.02	0.66	-0.20	0.31	Foreign	-0.10	0.69	0.34	0.07
BasInfr	0.32	-0.71	-0.09	-0.03	SchLeav	0.01	-0.04	0.67	-0.08	OverCro	-0.48	-0.09	0.73	0.11
SchLeav	-0.27	-0.71	-0.14	-0.02	CarUsag	-0.36	0.10	-0.64	-0.02	CarUsag	-0.34	0.01	-0.66	-0.09
Commut	-0.07	0.03	0.85	-0.01	OverCro	-0.54	-0.16	0.61	0.23	BasInfr	0.40	-0.30	0.45	0.14
OtheMuni	-0.18	0.09	0.84	0.09	BasInfr	0.33	-0.27	0.41	0.08	SchLeav	0.04	0.06	0.30	-0.20
Foreign	-0.02	0.08	-0.05	0.88	OtheMuni	-0.21	0.08	-0.11	0.84	OtheMuni	-0.19	0.08	-0.19	0.84
5yrMuni	-0.04	0.38	0.27	0.67	Commut	-0.04	0.07	0.12	0.82	Commut	0.18	0.03	0.26	0.74
Cardin.	-	-	+	+		+	Inc.[a]	+	+		+	Inc.[a]	+	+
% var. explained	30.8	19.5	9.5	7.3		32.8	15.5	10.7	7.1		33.5	13.3	11.6	8.0

[a] Inconclusive.

The shaded cells identify the strength of the loading in each variable. Only loadings >|0.4| are shaded

and internal mobility (PC3 in the joint PCA) are present in PC4 in all three censuses. Finally, daily commuting, which was represented in PC4 in the joint PCA, surges in PC3 in the 1991 separated PCA, with weaker loadings in 2001 and 2011.

In all three PCAs (Table 7), the more explicative principal component (PC1) is associated with age and education. In PC1 the variable WomEmp (women participation in the labor market) gains relevance from 1991 to 2011 (Table 7). A loading of –0.64 in 1991 in PC1 evolves to loadings of 0.81 and 0.76 in 2001 and 2011, but leading another SV driver represented by PC2, along with variables related to qualified jobs (SociVal), transportation and economic condition (CarUsag), and higher education (HighEdu), always with the same positive sign (Table 7). It is also worth noting that within PC1 in 1991, WomEmp presents an opposite sign with regard to the other explicative variables (Mean-Age, Fam65, Illiter, and PopChan), meaning that in the civil parishes where women's participation in the labor market is low, the mean age, older families, and illiteracy are high, and vice versa.

The most interesting feature in PC2 is the increasing role of the variable expressing the percentage of resident population of foreign nationality in explaining SV in 2001 and 2011–which in 1991 is associated with PC4 along with the percentage of resident population who 5 years before

lived outside the municipality (5yrMuni). Having the foreign population associated with population with higher education and professionals socially valued still misses a clear understanding. It may express contexts of large civil parishes where wealth neighborhoods coexist with low-class neighborhoods in which immigrants reside; or it may mean that in some civil parishes foreign communities are not necessarily associated with high social vulnerability. The interpretation of PC2 in 1991 is clearer than in the following analysis, particularly because the variable regarding the use of a car in daily journeys (CarUsag) is part of this PC with a positive loading as well.

The principal components regarding internal mobility—whether of a long-term (5yrMuni) or of a daily basis (Commut)—are represented by PC3 in 1991 and by PC4 in 2001 and 2011 but, besides the reduction in the percentage of variance explained, no other relevant changes are observed.

Variables, as indicators of social vulnerability, that improved significantly in the country seem to become less explicative of SV over time. Those are the cases of the percentage of conventional dwellings without at least one basic infrastructure (BasInfr) and the school leavers rate (SchLeav), whose loadings reduced from 1991 to 2001 and are <|0.5| in 2011. In summary, the self-grouping of variables in principal components is similar for the 2001 and 2011 Census, and slightly different in 1991.

6 Conclusions

This research tested a normalization method that spans multiple time frames. The normalization approach was applied elsewhere (Frigerio et al. 2018) and is not an innovation of our research. However, to the best of our knowledge, for the first time it was used in the procedure of multiplying the number of individuals according to the considered number of censuses (using 12,111 civil parishes in a joint PCA instead of the 4037 civil parishes of each census in separated PCAs). This procedure provides a reliable picture of the spatiotemporal dynamics of SV, maintaining a coherent set of SV drivers in the resulting principal components. When we perform separate PCAs, the SV drivers also change, which may be useful in analyzing the changes in the composition and type of SV drivers, but does not allow the monitoring of changes, in the same driver, over time.

The method is valid since the entire amplitude of values is considered, although the same civil parish is considered a different individual in the other time frames. However, even this approach does not solve the issue of not achieving absolute SV scores because when the data from the 2021 Census become available, the AMPI-normalized input data values will be different from the current ones (if new minimum or maximum values are observed), as well as the final SV scores. The innovative facet of this research consists of the replication of individuals in the principal component analysis, according to the number of considered time frames (three in this study).

In Portugal, the last global financial and public debt crisis hit the country later than in most countries, after 2011, and its impacts were not adequately covered at the civil parish scale by the 2011 Census, and the 2021 Census will be marked by the pandemic crisis. An expectation exists on how the local census data will express the socioeconomic and territorial drivers of social vulnerability in 2021. The research presented in this article showed a generalized decrease in SV from 1991 to 2011. An update to this study is planned using the new census data—despite the challenges posed by the changing spatial configuration of the civil parishes—focusing attention not only on the absolute SV changes but also on the drivers expressed by principal components as well.

Effective disaster risk management depends on the strengthening of the science-policy interface and supporting the policy cycle (EU 2020) in which social vulnerability knowledge will be applied. A comprehensive monitoring of spatiotemporal changes in SV will enable the adoption of corrective measures and the assignment of the respective public and private resources, contributing to an effective implementation of disaster risk reduction strategies (Spiekermann et al. 2015). However, further methodological developments are still needed to evaluate the predictive value of SV in estimating the degree and propensity to loss.

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