Chapter 3
Social Vulnerability in the Lisbon Metropolitan Area

Pedro Pinto Santos and Tiago Miguel Ferreira

Abstract The manifestation of a hazardous process in a given location is clear evidence of a threat to individuals and communities. Without hazard, there is no risk. Vulnerability, however, plays a less evident role in explaining the losses that are observed in databases, whether global or local. Social vulnerability, in particular, represents the underneath conditions that turn individuals and communities more or less able to endure the impacts of hazardous events. A detailed-level analysis of social vulnerability was performed in the Lisbon Metropolitan Area, considering the dimension of the individuals' characteristics—that we define as criticality—and the characteristics of the surrounding territories in the ability to provide support during and timely recovery after the event—that we define as support capability. The study area is highly contrasting in terms of this later dimension, with urban areas concentrating most of the services and equipment that reduce vulnerability. Regarding criticality, the methodology allowed to identify very-localized hotspots laid out to high propensity to losses from two drivers: employment and education (first principal component of criticality) and age, gender, and old urban fabric (second principal component). Analysed separately or combined in a single social vulnerability index, this information is useful in the planning of short-term actions in the strict field of civil protection operations and in mid- to long-term actions considering a wider perspective of risk governance, bringing to the table public policies in the areas of social care, mobility, urban planning, education, and health services, that address the very deep roots of vulnerability.

Keywords Social vulnerability · Criticality · Support capability · Risk assessment · Risk management

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1 Introduction

Vulnerability assessments are a keystone in the analysis of adaptation strategies not only for climate change [6, 16] but for disaster risk reduction (DRR) strategies as well, which is recognized as one of the four accelerators for the Sendai Framework implementation [17]. In fact, both global determinations—climate change adaptation and DRR—feature immense synergies and can only be effective if aligned at all scales and levels of intervention.

Social vulnerability is defined as the propensity of individuals, communities, and systems to be negatively affected by hazardous processes of diverse nature, based on their social and demographic characteristics [1, 2, 8, 10, 11]. Levels of social vulnerability act as predictors of the capacity of individuals, communities, and systems to cope with and recover from *inter alia*, the impact of disasters induced by natural processes [4], and are equally applicable to natural-induced or pandemic crisis situations such as the one experienced (to be still experienced?) recently. In this sense, social vulnerability and resilience are related as concepts and usefulness in risk assessment and management processes [3].

Social vulnerability (SV) is a key indicator for risk governance, involving the processes and impacts resulting from events of natural, technological, and environmental origin. The relevance of the analysis of social vulnerability at a sub-municipal level arises from the instrumental need to base policy options translated into strategic and operational measures in the context of risk prevention, reduction, mitigation, and adaptation [7], as well as the need to consolidate the indicators of support capability and community resilience. Therefore, this indicator responds to requirements in areas such as civil protection and emergency planning, social, health, and education policies, as well as contributing to the urban and spatial planning reference frameworks.

Current challenges in social vulnerability assessment lay on the ability to produce timely comparable vulnerability scores [5, 15], to find validation methodologies and data [13], to tailor the assessments to particular types of hazards [12], for instance in regard to flooding), and to incorporate socioeconomic projections in the models [18].

The aim of this study is to assess social vulnerability based on the perspective of Mendes [9], i.e., incorporating the individual dimension (criticality) and the collective dimension (support capability) of the proneness to suffer loss and the ability to recover in a timely manner. This SV assessment—and of its main drivers as expressed and mapped by the principal components—was done for the Lisbon Metropolitan Area (LMA) at the fine scale of the statistical block. Specific objectives are the collection of base information in support of the housing and residents' characteristics; the quantification and description of the main drivers of SV; the identification of the main socially vulnerable areas; and the provision of information to support the definition of local and regional policies for SV reduction—in the domains of health, elderly population, education, civil protection, urban planning, mobility, environment, and social assistance), acting upon the particular and most relevant SV drivers in any particular neighbourhood, city centre, or village in the LMA.

2 Study Area and Units of Analysis in the SV Assessment

The Lisbon Metropolitan Area (LMA) comprises 18 municipalities and 118 civil parishes. The resident population was, at the time of the SV assessment, 2,813,000 inhabitants, living in around 3,105 km^2 (a population density of 906 inhabitants./km^2). However, vast portions of the LMA are under ecological legal protection (marshland and nidification areas near the Tagus estuary), as well as the mountainous areas of Sintra (covering parts of the Sintra, Cascais, and Mafra municipalities) and Arrábida (covering parts of the Setúbal and Sesimbra municipalities).

In the LMA, there are 4521 statistical blocks (Fig. 1). They differ significantly in area and population, with urban areas being represented by smaller and more densely inhabited blocks, and rural and natural protected areas with vaster areas and a small number of inhabitants. There are two statistical blocks with zero inhabitants: in these cases, criticality is assigned the lowest score, but support capability is calculated likewise the units of analysis. On average terms, the mean area of statistical blocks is 0.64 km^2 and the mean population is 624 persons, a figure that, considering the LMA population of more than 2.8 million, expresses the high level of detail of the SV assessment.

3 Methodology for the Social Vulnerability Assessment

Social vulnerability (SV) was evaluated for the entire LMA using the census statistical block level, and it is the result of the product of criticality (Cr) and support capability (SC) [10], as formulated in Eq. **1**.

$$SV = Cr \times (1 - SC) \tag{1}$$

As intermediate results, for each of the 4521 statistical blocks that compose the LMA, scores are calculated for each principal component (PC) within criticality and support capability, in addition to the final SV score itself. The SV index aims to overcome the constraint of subnational scales of analysis by incorporating a territorial perspective in support capability dimension of SV. The proposed method incorporates not only the individual characteristics of the population and risk groups as it also considers the territorial context in which they are supported, i.e., the public and private equipment, infrastructure, and services that might play a role in attenuating losses and enhancing recovery [9].

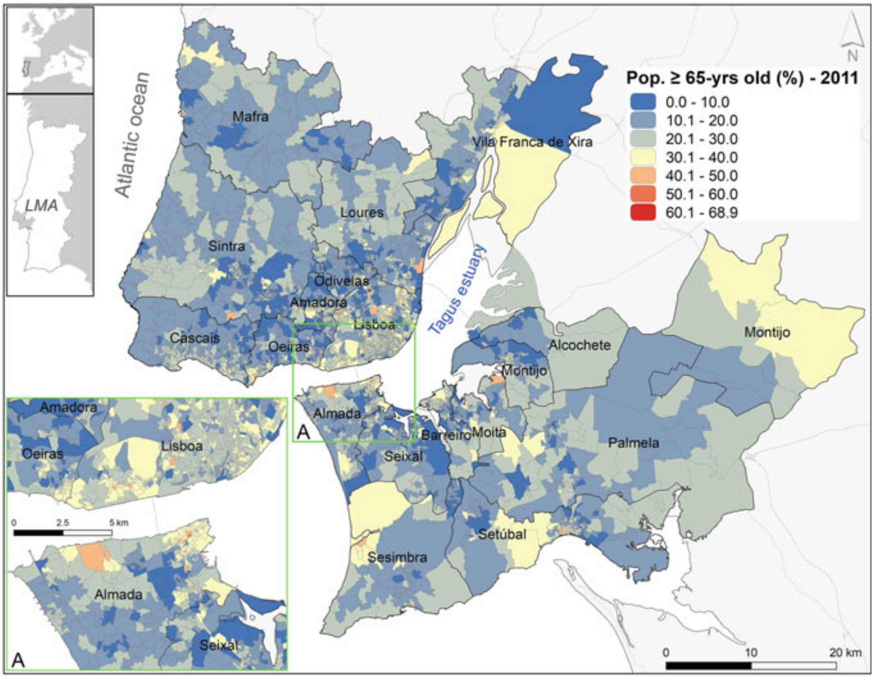

Fig. 1 Illustration of the fine scale of representation allowed by the selection of statistical block as the unit of analysis in the social vulnerability assessment. Representation of the proportion of population with or over 65 years old in the Lisbon Metropolitan Area

3.1 Criticality

Criticality (*Cr*) expresses the characteristics of individuals that make them prone to loss, considering their age, socioeconomic condition, health and housing conditions, social assistance, mobility, educational level, and employment. Data regarding an initial set of 43 variables was collected to perform the assessment of criticality (Table 1), which attempts to cover directly or indirectly those domains of vulnerability. In order to be comparable among statistical blocks, values of variables are expressed as proportions of the absolute value of the base variable (this means a % of the total residents, total dwellings, total buildings, etc.).

3.2 Support Capability

Support capability (*SC*) expresses the set of systems, networks, public and private infrastructures, and collective equipment aimed at supporting communities and their activities, which, in the eminence or occurrence of a dangerous process, make it

Table 1 List of variables used in the criticality assessment in the LMA

Code	Description of the variable
Vacant	Vacant dwelling units (%)
No Water	Dwelling units without water supply (%)
No Sewage	Dwelling units without sewage system (%)
Rented	Rented dwelling units (%)
1 or 2 Div	Dwelling units with 1 or 2 divisions (%)
5 plus Div	Dwelling units with five or more divisions (%)
Less 50 m^2	Dwelling units with less than 50 m^2 (%)
Plus 200 m^2	Dwelling units with more than 200 m^2 (%)
Plus 100 m^2	Dwelling units with more than 100 m^2 (%)
With Bath	Dwelling units with bathing facilities (%)
Owner	Dwelling units occupied by the owner (%)
Before 1970	Buildings built before 1970 (%)
1 or 2 floors	Buildings with 1 or 2 storeys (%)
5 plus floors	Buildings with five or more storeys (%)
Concrete	Buildings with a concrete structure (%)
Stone	Buildings with a structure of adobe and loose stone (%)
Study 9th	Individuals studying (1st 9th degree) (%)
Study muni	Individuals studying in the municipality of residence (%)
Complete 9th	Individuals with nine years of education completed (%)
Higher edu	Individuals with higher education completed (%)
Illiter	Illiterate individuals (%)
Primary sector	Individuals employed in the primary sector (%)
Secondary sector	Individuals employed in the secondary sector (%)
Tertiary sector	Individuals employed in the tertiary sector (%)
Unemployed	Individuals between 25 and 64 years old unemployed or looking for their first job (%)
Employed	Individuals between 25 and 64 years old employed (%)
Work muni	Individuals working in the municipality of residence (%)
Work study muni	Individuals working or studying in the municipality of residence (%)
No activ	Individuals without economic activity (%)
Work study out	Individuals working or studying outside the municipality of residence (%)
Indiv family	No. of individuals per family (no.)
5 plus family	Families with five or more elements (%)
1 or 2 family	Families with 1 or 2 elements (%)
65 plus family	Families with elements with 65 or more years old (%)
All employed	Families without unemployed elements (%)

(continued)

Table 1 (continued)

Code	Description of the variable
Child in family	Families with children less than 15 years old (%)
Pop 0 to 4	Individuals with less than five years old (%)
Pop 15 to 24	Individuals between 15 and 24 years old (%)
Pop 65 plus	Individuals 65 years old or older (%)
Indiv per dwell	No. of individuals *per* dwelling (no.)
Masculi rate	Masculinity rate (%)
Retired	Retired individuals (%)
Women pop	Women population (%)

possible to reinforce the community's capacity to mitigate and/or recover from a hazardous event. Common dimensions covered are the economic dynamism, the coverage by social equipment (for example, health centres), civil protection resources, and public and private businesses that provide essential goods and mobility. The equipment and services included in the assessment (Table 2) are expressed according to different methods of accounting for

- the coverage by fire stations, pharmacies, hospitals, health infrastructures, gas and power stations, and police stations is expressed by the distance from the centroid of the statistical block to the nearest entity;
- the coverage by the touristic equipment with capacity for temporary shelter expresses the sum of the lodging units in the hotels located inside or within 3 km from the boundaries of each statistical block;
- the coverage by the main road network is evaluated considering the location of the nearest nodes of the secondary and tertiary road hierarchy (node levels 3 and 4). This excludes node level 5 of connectivity (primary hierarchy, a level between highways only) and the urban node levels (1 and 2), which are less relevant in describing municipal and inter-municipal accessibility. The underneath rationale

Table 2 List of variables used in the support capability assessment in the LMA

Code	Description
Hotel housing	Coverage by hotels with capacity for temporary shelter
Fire sta	Coverage by fire stations
Pharm	Coverage by pharmacies
Road nodes 34	Coverage by the main road network
Hospital	Coverage by hospitals
Health centre	Coverage by health centres
Gas sta	Coverage by car gas and power stations
Police	Coverage by police stations
Grocery	Coverage by grocery stores

is to express i) the ability to be accessed by outside support (rescue and emergency operations, provision of essential goods) and ii) to be able to evacuate in emergency situations or to move in daily activities;
- the coverage by grocery stores also follows the nearest distance, but it also classifies the stores into two levels: class 1 for small bakeries, butcheries, and convenience stores; level 2 for municipal markets, supermarkets, and shopping centres.

All geographical entities are expressed as points, and they were collected using a buffer of 30 km from the boundaries of the LMA (except the grocery stores that followed a buffer of 7 km), in order to avoid the prejudice of near-boundary areas well covered by LMA-outside services and equipment. Unlike the data supporting the criticality assessment, which is based solely on Census information, the collection and integration of the geographical input data for the support capability assessment are far more time-consuming, and not entirely exempt from representation bias caused by the metrics in which the coverage is expressed.

The extent of the damage—for example, the number of casualties or the number of days with restricted mobility—will depend on the support capability of the territory. A high support capability may thus constitute a counterpoint to a high level of criticality. The location and density of infrastructures are a reflection of the way society is structured. While for a population with a high support capability, a certain damaging event may only take on fortuitous characteristics—since it has sufficient capacities and resources to be able to more or less easily restore the losses and damages suffered—in the case of a population framed in a territory with reduced support capability, that same event may mean the aggravation of existing fragilities, giving rise to situations of serious disruption of daily socioeconomic functions.

3.3 Statistical Procedure

Prior to the application of Eq. 1, autonomously for each dimension *Cr* and *SC*, the following steps are taken:

- normalization of data to the z-score;
- test of multicollinearity between input variables until a set of robust variables is achieved, excluding pairwise variables with Pearson correlation coefficients higher than 0.7;
- iterative application of Principal Component Analysis, using anti-image matrices' correlations, communalities' scores, KMO, and interpretation of the rotated component matrix to exclude unsuitable or irrelevant variables from the analysis, as well as additional redundant variables;
- after the final model is achieved, interpretation of the principal components and attribution of their cardinality, according to their role in explaining Cr and SC;

- sum of component scores with weighting defined by the % of variance explained by each principal component;
- linear transformation of values to an interval between 0 and 1;
- classification of the score of each unit of analysis according to its standard deviation.

The number of principal components (also named PCs) is defined from the eigenvalues above 1.

4 Results

4.1 Criticality

Following the statistical procedure described, the final PCA model for criticality was run with 12 variables, as presented in Table 3.

For that dataset, a KMO score of 0.722 is achieved, 73.7% of the total variance is explained, and four principal components (PC) with Eigenvalue >1 were extracted.

PCs represent the four drivers of criticality, as interpreted from the rotated components matrix (Table 4), and they were named as follows:

- employment and qualifications (PC1), which explains 32.5% of the total variance;
- age, gender, and ageing urban context (PC2), 22.5% of the total variance;
- housing conditions (PC3), 10.3% of the total variance;
- and family structure (PC4), 8.4% of the total variance.

Table 3 Final set of variables used in the criticality assessment, after redundancy elimination and analysis of robustness

Code	Variable	Communalities
(Rented)	Rented households (%)	0.802
(Less 50 m^2)	Dwelling units under 50 m^2 (%)	0.690
(With bath)	Dwelling units with bathing facilities (%)	0.590
(Before 1970)	Buildings built before 1970 (%)	0.725
(Concrete)	Building with a concrete structure (%)	0.617
(Complete 9th)	Individuals with nine years of education completed (%)	0.885
(Higher edu)	Individuals with higher education completed (%)	0.824
(Secondary sector)	Individuals employed in the (%)	0.751
(Employed)	Individuals between 25 and 64 years old employed (%)	0.692
(5 plus family)	Families with five or more elements (%)	0.812
(Pop 65 plus)	Individuals 65 years old or older (%)	0.815
(Women pop)	Women population (%)	0.644

Table 4 Rotated component matrix for the assessment of criticality. For the sake of interpretation, some variable names were simplified

	Principal components (PCs)			
	1	2	3	4
Pop. With Higher Education (%)	−0.889	0.119	−0.09	−0.111
Pop. With Elementary School (%)	0.860	0.289	0.246	0.031
Pop. Employed in the Industry (%)	0.717	−0.472	0.023	−0.117
Pop. Employed (%)	−0.703	−0.245	−0.096	−0.357
Pop. Over 65 years old (%)	0.233	0.822	0.188	−0.22
Women population (%)	−0.145	0.777	−0.122	−0.065
Buildings built before 1970 (%)	0.014	0.643	0.537	−0.152
Rented households (%)	0.154	0.549	0.511	0.464
Concrete buildings (%)	0.042	−0.091	−0.767	0.135
Households with bathroom (%)	−0.231	0.175	−0.708	−0.069
Households under 50 m^2 (%)	0.290	0.342	0.663	0.22
Families with five or more elements (%)	0.143	−0.311	−0.046	0.832
Cardinality	+	+	+	+
% of the total variance explained	32.492	22.474	10.315	8.446

The final cartographic expression of criticality at the statistical block in the LMA is represented in Fig. 2 and summarized in Figs. 3 and 4, and in Table 5.

The resident population in each statistical block can be summed according to the respective class of criticality in the entire LMA (Fig. 3) and by municipality (Table 5). An obvious remark to this summing is that not all residents with a unit of analysis feature the same levels of criticality. However, these figures represent a fair indication of the dominant levels of criticality.

A total of 150,649 inhabitants (5.3% of the population of 2,821,876) reside the in the 273 statistical blocks (6.0% of the total, 4521) classified with very high criticality. They are located particularly in some old neighbourhoods of Lisbon, as well as in some suburban areas in the municipalities of Almada, Amadora, Barreiro, Loures, Moita, and Setúbal. Very high criticality is rarely found in rural areas.

On the other side of the scale, very low criticality is assigned to 324 statistical blocks (7.2% of the total), where 217,214 inhabitants reside (7.7% of the total). In a simple generalization, these blocks are located in three types of geographical typologies: historically areas of low urban density located outside or in the near outskirts of the main cities (the examples of statistical blocks located in the Cascais, Sintra, and Oeiras municipalities); newly constructed areas of low density, frequently closed condominium (the case of some blocks in Cascais, Oeiras, Mafra, Montijo, Alcochete, and Almada); newly constructed areas of high urban density, i.e., tall buildings (exemplified by some neighbourhoods in northern Lisbon, eastern Lisbon, and Oeiras).

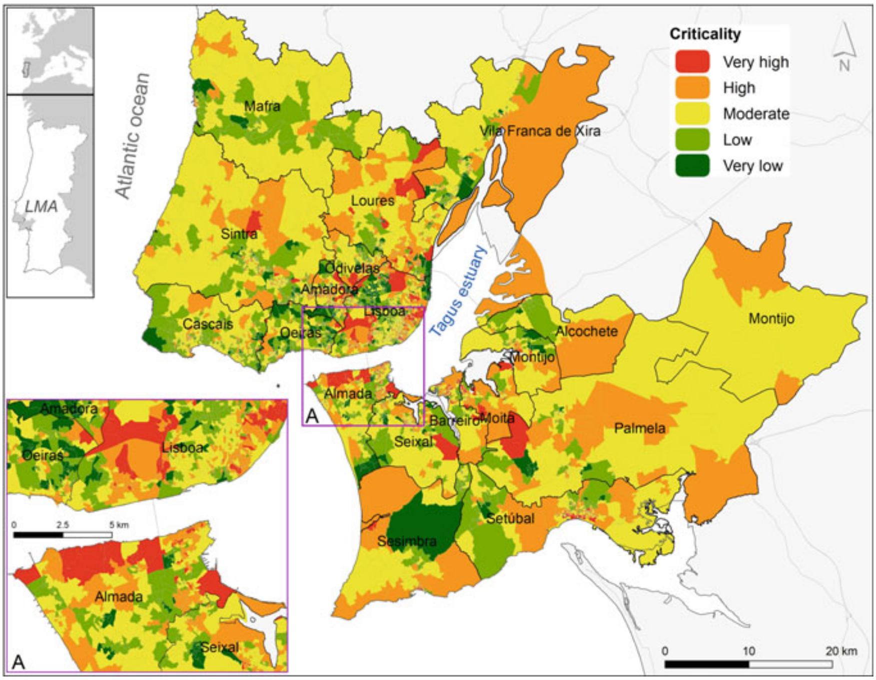

Fig. 2 Criticality in the Lisbon Metropolitan Area

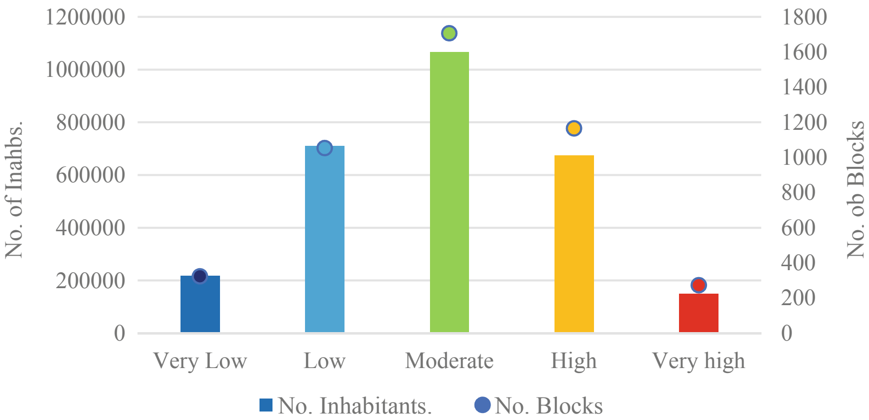

Fig. 3 Number of inhabitants and statistical blocks by class of criticality in the LMA

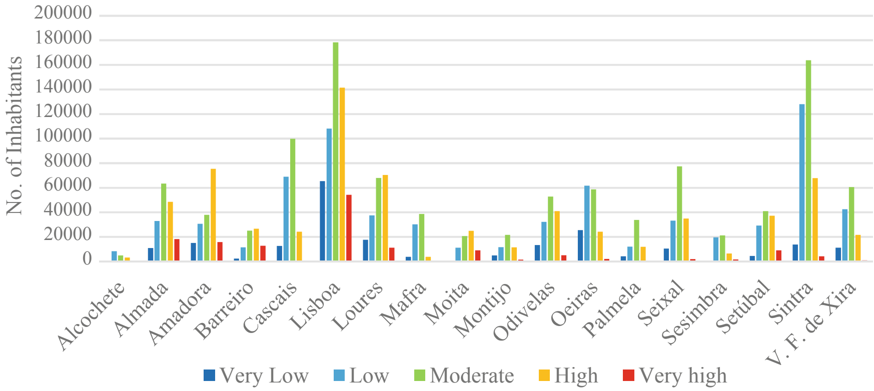

Fig. 4 Number of inhabitants by class of criticality in the LMA municipalities

Given the great detail of the analysis, considering the total of 4521 statistical blocks in the study area, the municipality of Sintra was chosen as an example to map the behaviour of each territorial unit in each of the criticality drivers (PC1–PC4); see Figs. 5, 6, 7 and 8.

Together, the four maps presented above show that a given territorial unit—whether a neighbourhood, a village, or a very small rural settlement between cities and villages—can feature high scores in one criticality driver and low scores in another. The combinations are multiple and define the criticality profile summarized in Fig. 2. For instance, the northern near-half portion of the municipality is essentially rural or newly urbanized areas where unemployment and low qualifications predominate (Fig. 5), which are not necessarily areas with bad housing conditions (poor housing conditions exist in the NE sector but not in the NW sector) (Fig. 7).

4.2 Support Capability

Following the statistical procedure described, the final PCA model for support capability was run with nine variables, as presented in Table 6.

For that set, an excellent KMO score of 0.912 is achieved, and 65.9% of the total variance is explained by the two principal components (PCs) with Eigenvalue >1 that were extracted. PCs represent the two drivers of support capability, as interpreted from the rotated components matrix (Table 7), and they were named as follows:

- general equipment and services coverage (PC1), which explains 54.7% of the total variance;
- coverage by equipment with capacity for temporary shelter (PC2), 11.1% of the total variance.

Table 5 Summary of the number of inhabitants and statistical blocks by class of criticality in the 18 municipalities of the LMA

Municipalities	Very low		Low		Moderate		High		Very high		Totals	
	No. blocks	No. inhab.	No. blocks	No. inhab.	No. blocks	No. inhab.	No. blocks	No. inhab.	No. blocks	No. inhab.	Blocks	Inhab.
Alcochete	1	477	12	8476	7	4897	6	3153	1	566	27	17,569
Almada	18	10,971	63	32,958	115	63,392	90	48,487	32	18,222	318	174,030
Amadora	26	15,172	46	30,578	58	38,083	121	75,450	28	15,853	279	175,136
Barreiro	3	2437	18	11,585	41	25,119	47	26,701	25	12,922	134	78,764
Cascais	17	12,626	106	69,022	156	99,957	40	24,174	1	700	320	206,479
Lisboa	113	65,526	213	108,169	361	178,282	274	141,469	93	54,287	1054	547,733
Loures	24	17,756	53	37,539	94	67,986	104	70,460	20	11,313	295	205,054
Mafra	5	3716	38	30,189	59	38,654	9	3796	1	330	112	76,685
Moita	0	0	13	11,307	30	20,674	40	24,980	18	9068	101	66,029
Montijo	6	4894	15	11,700	31	21,670	20	11,544	3	1414	75	51,222
Odivelas	18	13,383	38	32,308	68	52,781	66	41,005	8	5072	198	144,549
Oeiras	36	25,538	96	61,637	98	58,696	41	24,197	2	2052	273	172,120
Palmela	8	4233	16	12,074	50	33,898	20	11,996	2	630	96	62,831
Seixal	15	10,538	49	33,330	116	77,464	57	34,915	4	2022	241	158,269
Sesimbra	1	338	27	19,722	36	21,197	17	6498	6	1745	87	49,500
Setúbal	5	4528	41	29,303	63	40,923	63	37,264	20	9167	192	121,185
Sintra	15	13,883	158	127,997	237	163,791	111	67,849	7	4315	528	377,835
VF Xira	13	11,198	51	42,644	86	60,441	39	21,632	2	971	191	136,886
Total	324	217,214	1053	710,538	1706	1,067,905	1165	675,570	273	150,649	4521	2,821,876

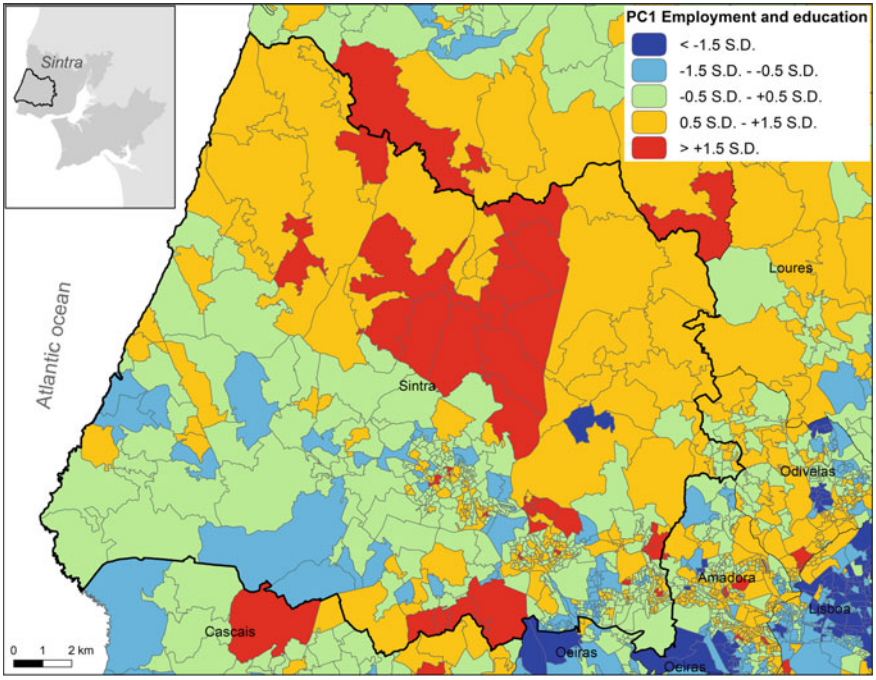

Fig. 5 Cartographic expression of the PC scores in regard to employment and education (PC1 of criticality) in the Sintra municipality

Cardinality in both PCs needed to be inverted because the shortest the distance to the equipment or service, the higher the support capability (the case of PC1, in which the explicative variables present a positive sign in the loading), and the higher the number of shelter units the higher the support capability (the case of PC2, in which the strongest explicative variable presents a negative sign in the loading).

The final cartographic expression of support capability at the statistical block in the LMA is represented in Fig. 9.

The final cartographic expression of support capability at the statistical block in the LMA is represented in Fig. 9 and summarized in Figs. 10 and 11, and Table 8.

The resident population in each statistical block can be summed according to the respective class of support capability in the entire LMA (Fig. 10) and by municipality (Table 8). As expressed in regard to criticality, naturally not all residents within a given class are characterized by it, despite the dominance of the class in the block.

A total of 726,600 inhabitants (25.7% of the population) reside in the 1308 statistical blocks (28.9% of the total) classified with very high support capability. This dimension is SV features a macrocephalic pattern spreading from the capital city of Lisbon to the metropolitan area. In the northern sector of LMA, starting from Lisbon, the spreading of areas with very high and high SC follows three alignments defined

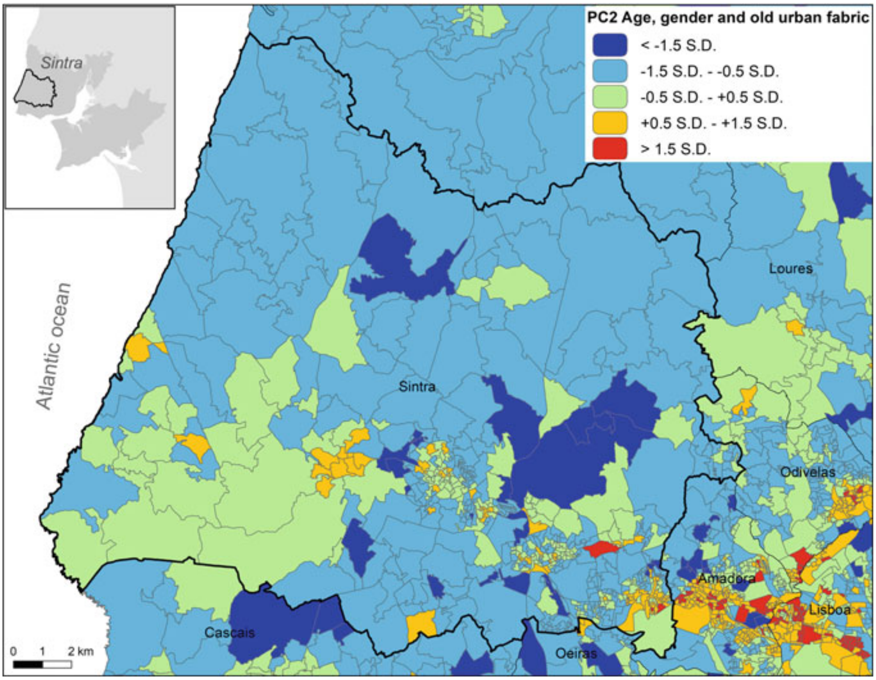

Fig. 6 Cartographic expression of the PC scores in regard to age, gender, and old urban fabric (PC2 of criticality) in the Sintra municipality

by the main communication routes (railway in the first phase, and road later): from Lisbon to V.F. Xira; from Lisbon to Sintra, including Amadora; and from Lisbon to Cascais, including Oeiras. Those alignments express the expansion of urbanization in the north LMA. In the south LMA, the pattern follows a similar process but in regard to the fluvial transportation and the location of the Tagus river bridge (between Almada and Lisbon). The city of Setúbal, by its proper economic dynamism, concentrates a high diversity and quantity of services and public equipment that result in high and very high support capability.

Very low scores of SC are found in the remaining interstitial areas, with small urban settlements, villages, or dispersed edification. They sum a total of 149 statistical blocks (3.3%) where 90,845 persons reside (3.2%).

The support capability drivers, expressed by the two principal components (PC1 and PC2), are mapped in Figs. 12 and 13.

As can be observed in the figures above, following the classification according to the standard deviation (S.D.), no statistical blocks in the LMA scored higher than 1.5 S.D. in regard to the general equipment and services coverage (PC1). Most blocks fall in the intermediate class (−0.5 to 0.5 S.D.), and it is concluded that the most urbanized areas, like Lisbon's city centre, are not necessarily the most covered by the

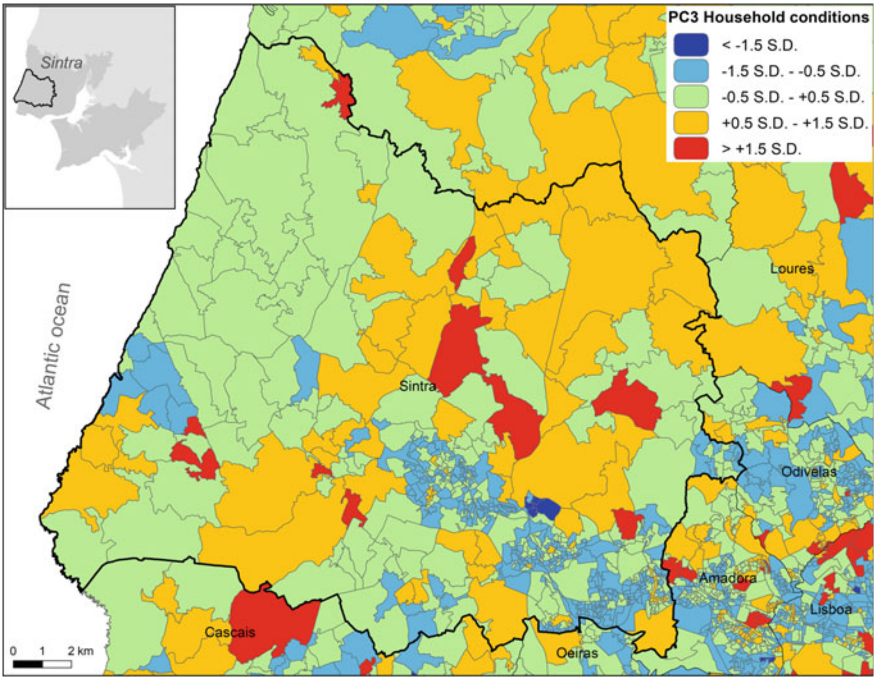

Fig. 7 Cartographic expression of the PC scores in regard to household conditions (PC3 of criticality) in the Sintra municipality

equipment and services included in the analysis. In terms of the temporary shelter provided by hotel facilities, the Lisbon municipality concentrates most of the lodging units available. According to the official data provided by the WebGIS SIGTUR of Tourism Portugal, the LMA presents a total of 63,962 lodging units—excluding camping areas and local lodgement provided in apartments—from which 26,902 (42.1%) are located in the Lisbon municipality. Less covered areas are located in the municipalities of Mafra, Sintra, Loures, Odivelas, Seixal, Sesimbra, and Palmela.

4.3 Social Vulnerability

As an expression of the product of criticality and support capability—as expressed in Eq. 1, and after the transformation to the amplitude [0, 1] of both dimensions—social vulnerability scores range between 0.00 and 0.55, with an average of 0.04. The three municipalities with the highest average are Palmela (0.11), Mafra (0.11), and Alcochete (0.09). On the opposite side, they are Lisbon, Amadora, and Oeiras (both with an average score of 0.02). Apart from the municipal average values, it

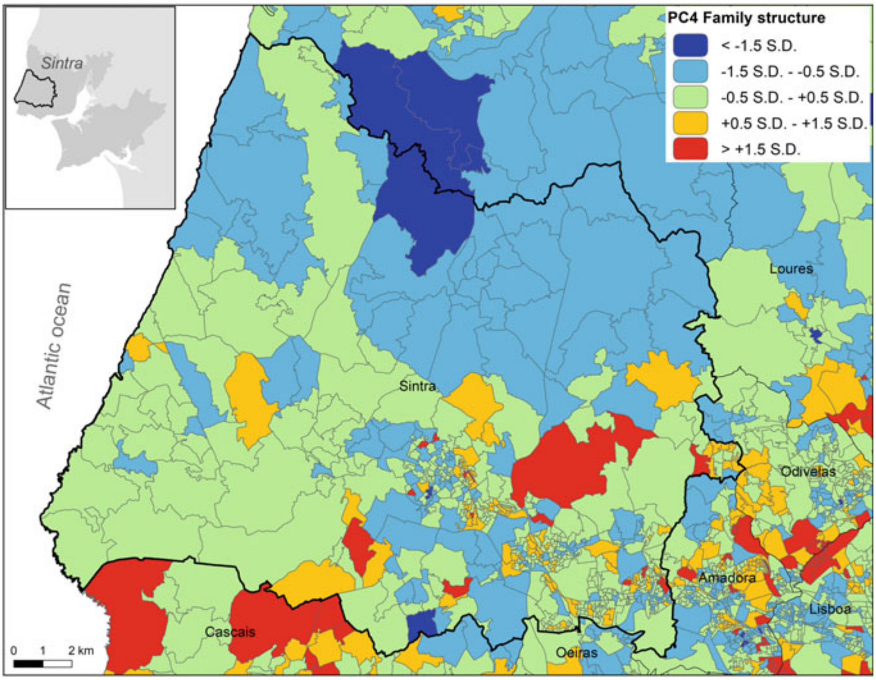

Fig. 8 Cartographic expression of the PC scores in regard to the family structure (PC4 of criticality) in the Sintra municipality

Table 6 Final set of variables used in the support capability assessment, after redundancy elimination and analysis of robustness

Code	Variable	Communalities
Hotel housing	Coverage by hotels with capacity for temporary shelter	0.904
Fire sta	Coverage by fire stations	0.632
Pharm	Coverage by pharmacies	0.756
Road nodes 34	Coverage by the main road network	0.491
Hospital	Coverage by hospitals	0.587
Health centre	Coverage by health centres	0.653
Gas sta	Coverage by car gas and power stations	0.630
Police	Coverage by police stations	0.691
Grocery	Coverage by grocery stores	0.583

is important to focus on the detailed level of analysis made possible by the small dimension of the statistical blocks.

Table 7 Rotated component matrix for the assessment of support capability

	Principal components (PCs)	
	1	2
Coverage by pharmacies	0.861	0.124
Coverage by police stations	0.810	0.186
Coverage by car gas and power stations	0.793	0.024
Coverage by fire stations	0.769	0.203
Coverage by grocery stores	0.762	0.053
Coverage by health centres	0.759	0.279
Coverage by the main road network	0.657	0.242
Coverage by hospitals	0.565	0.518
Coverage by hotels with capacity for temporary shelter	−0.051	−0.950
Cardinality	–	–
% of the total variance explained	54.741	11.135

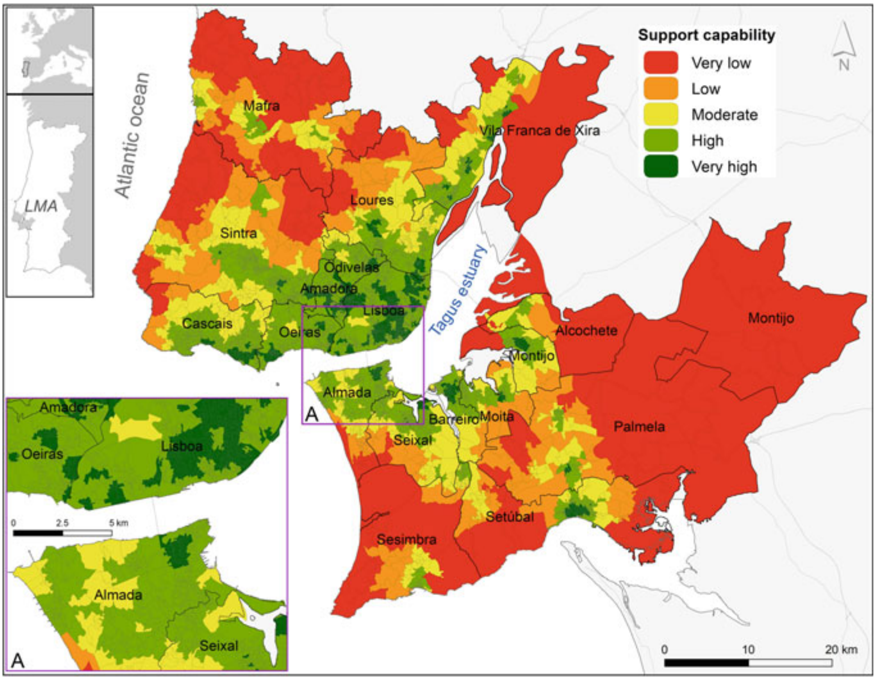

Fig. 9 Support capability in the Lisbon Metropolitan Area

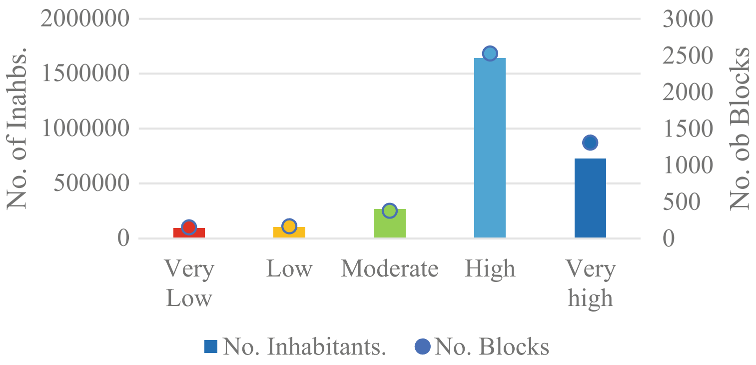

Fig. 10 Number of inhabitants and statistical blocks by class of support capability in the LMA

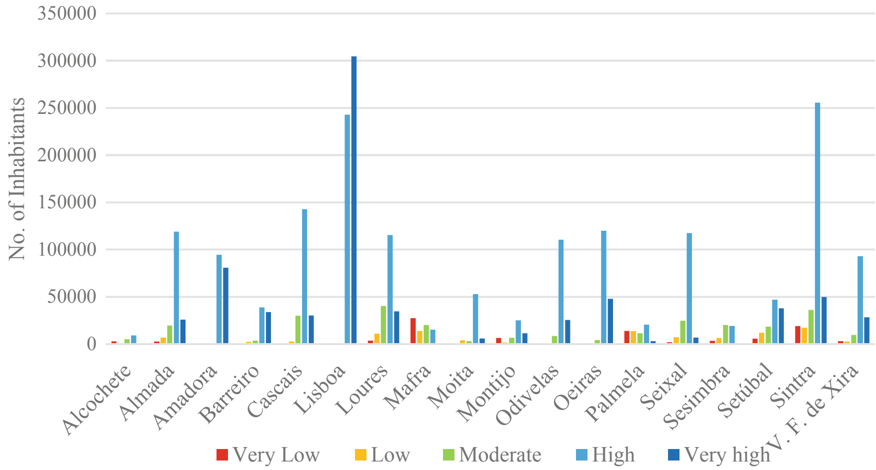

Fig. 11 Summary of inhabitants by class of support capability in the LMA municipalities

Public policies related to risk governance need to consider the statistical blocks resulting from the overlay of the least supported areas (low and very low support capability) and the most critical ones (high and very high criticality) because they represent the hotspots of social vulnerability in the Lisbon Metropolitan Area (Fig. 14).

Table 8 Summary of the number of inhabitants and statistical blocks by class of support capability in the 18 municipalities of the LMA

Municipalities	Very low		Low		Moderate		High		Very high		Totals	
	No. blocks	No. inhab.	No. blocks	No. inhab.	No. blocks	No. inhab.	No. blocks	No. inhab.	No. blocks	No. inhab.	Blocks	Inhab.
Alcochete	5	2875	1	492	7	5085	14	9117	0	0	27	17,569
Almada	7	2679	18	6879	38	19,635	209	119,028	46	25,809	318	174,030
Amadora	0	0	0	0	0	0	141	94,440	138	80,696	279	175,136
Barreiro	0	0	4	2408	7	3691	66	38,822	57	33,843	134	78,764
Cascais	1	456	4	2758	37	30,118	226	142,896	52	30,251	320	206,479
Lisboa	0	0	0	0	1	516	453	242,797	600	304,420	1054	547,733
Loures	6	3714	17	10,957	55	40,373	163	115,358	54	34,652	295	205,054
Mafra	40	27,394	19	13,863	27	20,127	26	15,301	0	0	112	76,685
Moita	0	0	6	3975	5	3105	80	52,883	10	6066	101	66,029
Montijo	9	6566	2	1547	11	6616	34	25,157	19	11,336	75	51,222
Odivelas	0	0	0	0	9	8635	147	110,467	42	25,447	198	144,549
Oeiras	0	0	0	0	5	4269	184	119,875	84	47,976	273	172,120
Palmela	21	13,872	22	13,692	18	11,617	30	20,448	5	3202	96	62,831
Seixal	3	1793	12	7187	36	24,793	178	117,596	12	6900	241	158,269
Sesimbra	11	3489	11	6561	29	20,146	36	19,304	0	0	87	49,500
Setúbal	11	5806	17	12,078	27	18,545	69	46,941	68	37,815	192	121,185
Sintra	30	19,115	26	17,232	49	36,136	344	255,555	79	49,797	528	377,835
VF Xira	5	3086	4	2729	15	9816	125	92,865	42	28,390	191	136,886
Total	149	90,845	163	102,358	376	263,223	2525	1,638,850	1308	726,600	4521	2,821,876

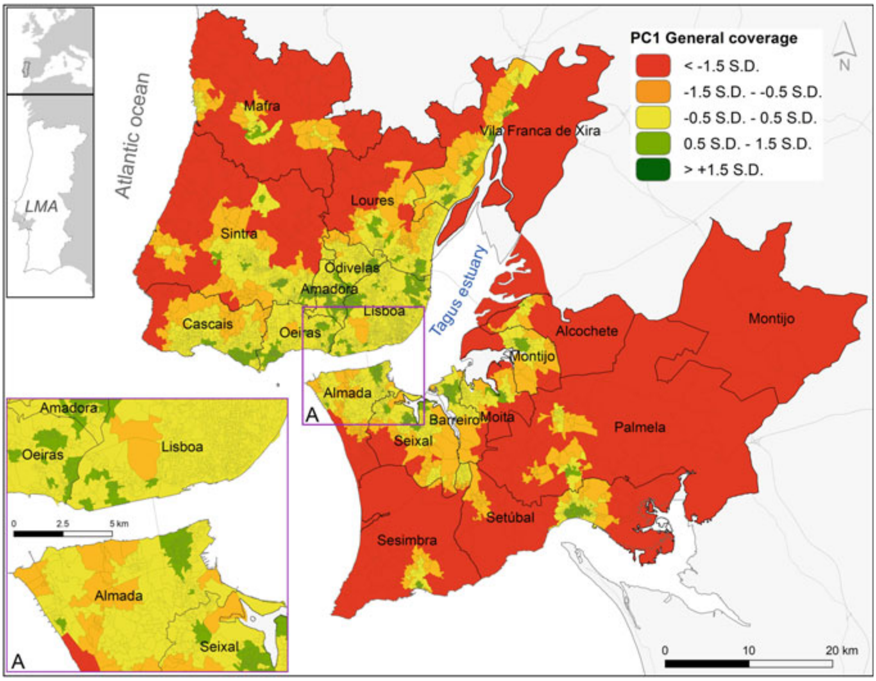

Fig. 12 Cartographic expression of the PC scores in regard to the general equipment and services coverage (PC1 of support capability) in the LMA

5 Conclusions

Social vulnerability is a key indicator for risk governance, involving the processes and impacts arising from events of natural, technological, or environmental origin [10, 14]. Several studies suggest that the levels of vulnerability of individuals and communities explain (in certain geographical and socioeconomic contexts) the impacts observed in databases, as much as the levels of susceptibility and exposure to hazard processes.

In this study, we applied a methodology for assessing social vulnerability in the Lisbon Metropolitan Area (LMA), based on principal component analysis, from 2011 Census data. The territorial unit of analysis is the statistical section, making up 4521 units, consisting of a very detailed-level, large-scale analysis for the entire LMA.

Starting from an initial set of 43 variables in the domains of age, gender, employment, educational qualifications, housing conditions, and mobility, the final model for criticality integrates 12 variables, extracting four principal components (PC), interpreted as follows: employment and qualifications (PC1), which explains 32.5% of the total variance; age, gender, and ageing urban context (PC2), 22.5% of the total variance; housing conditions (PC3), 10.3% of the total variance; and family

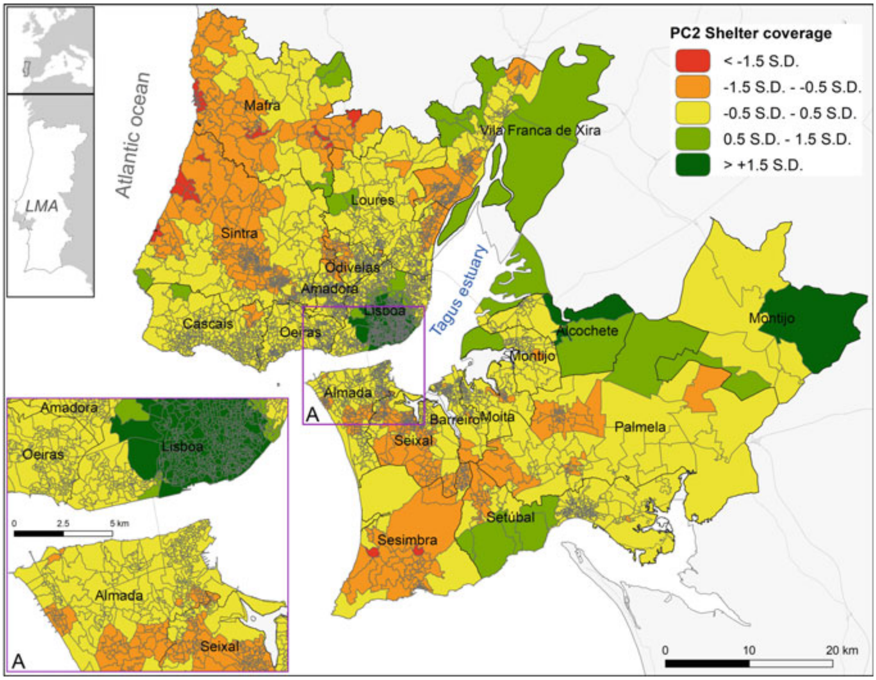

Fig. 13 Cartographic expression of the PC scores in regard to the shelter coverage (PC2 of support capability) in the LMA

structure (PC4), 8.4% of the total variance. The sum of the scores of each principal component provides a final index of criticality that allows the identification of the most vulnerable neighbourhoods and urban centres.

For the support capability assessment, an initial set of 9 variables were considered, and the resulting PCs express the general coverage by most of the considered services and equipment (PC1) and the particular coverage by the equipment with the ability to provide temporary shelter (PC2).

The analysis of the individual mapping of the scores of each component provides an understanding of the most active dimensions or drivers of criticality and support capability in each statistical section.

Social vulnerability studies are applied at two levels of public policy action: in supporting emergency civil protection planning for the phases of imminence, occurrence, and post-disaster recovery; in medium and long-term risk management planning, identifying, and understanding the drivers that explain the propensity of individuals and communities to loss and the degree of difficulty in recovery. Both levels translate into the definition of intra- and inter-municipal resource allocation priorities that promote increased resilience to various types of risks.

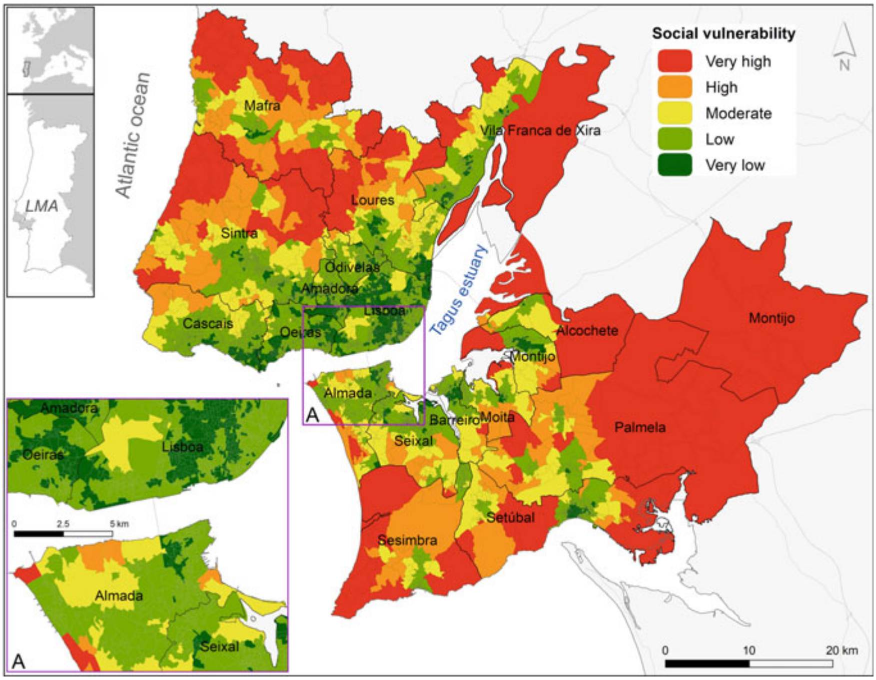

Fig. 14 Social vulnerability in the Lisbon Metropolitan Area

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