

# Assessment of Social Vulnerability to Flooding in a Estuarine Context

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**Abstract.** This paper describes the methodology and first results of a social vulnerability assessment in an estuarine area in Portugal. The nature of the hazard – marginal flooding in an estuarine context by tide, storm surge and urban drainage effect – and the scale adopted, posed interesting challenges to the application of the methodology proposed in the Social Vulnerability Index (SoVI<sup>®</sup>), namely the selection of the unit of analysis and the identification of the most adequate and pertinent initial input variables. Results indicate that the characteristics of the urban context, population age, family structure, economic power and mobility are the most explicative components of the social vulnerability distribution patterns in the Tagus estuary. Scale, quality and diversity of input data are key points in the interpretative capacity that can be achieved by the analysis of the vulnerability components.

**Keywords.** Estuarine margins flooding, local scale, Principal Component Analysis, Tagus river estuary

## 1 Introduction

Social vulnerability (SV) is a complex concept that can be summarized as a preexisting condition of individuals and communities that influences their preparation, response and recovery from hazard events [1], resulting both from social inequalities and place inequalities [2].

Vulnerability assessments must be conducted considering that vulnerability is as an “integral part of the causal chain of risk” and that its reduction is a cost-effective strategy of risk management [3]. Understanding SV is crucial in the development of disaster mitigation plans and policies. In fact, SV sources are not only addressed via civil protection action, but also require a broader concerted action between practitioners of distinct public and private sectors and fields such as health, education, social assistance, economy, spatial planning and transportation, just to mention the most relevant. Understanding SV is, therefore, of key importance in any risk governance process.

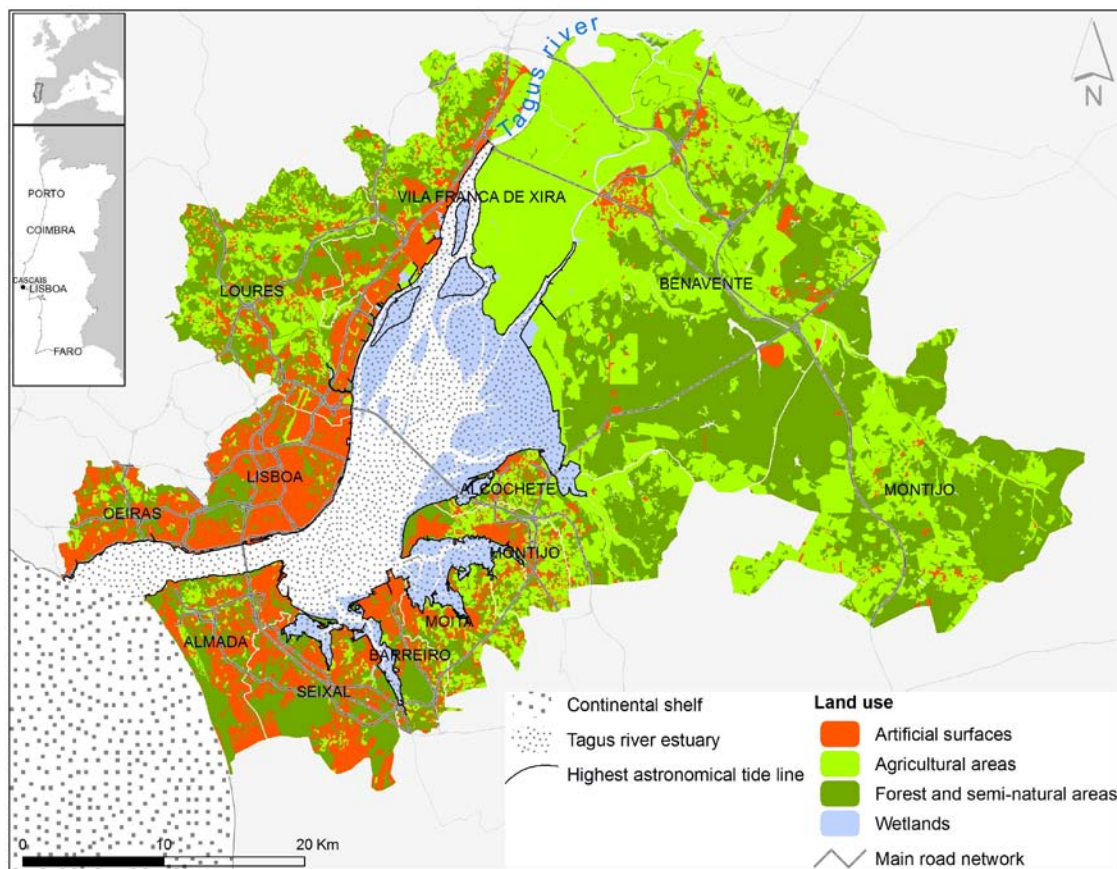
The development of indexes as a way of quantifying SV serves the purpose of simplifying the multidimensional complexity of SV into a single metric [4]. Since the Social Vulnerability Index (SoVI<sup>®</sup>) was proposed as a measure of expressing the potential for loss to environmental hazards [2], research on this specific type of vulnerability has expanded both conceptually and geographically. In Portugal, for example, a new SV index was proposed which considers the components of criticality and support capability, being the former the “ensemble of individuals’ characteristics and behaviors that may contribute to the system’s rupture” and the later the “set of territorial infrastructure that enables the community to react in case of disaster” [5, p. 446]. The SoVI<sup>®</sup> was recently applied in Portugal to a set of 149 civil parishes of the Greater Lisbon, where the final model was performed with 38 variables, after multicollinearity elimination [6].

SV explicative variables are related to concepts such as socioeconomic status, gender, race and ethnicity, age, community’s economic wealth, rural/urban dichotomy, household characteristics, infrastructure and lifelines,

household ownership and occupation, family structure, population change, access to medical services, education, social dependence and special needs populations [2]. A major challenge when attempting to characterize SV in a given area consists in finding the best balance between the scale of analysis and the adequacy, depth and pertinence of the variables that aim to represent each of those concepts.

In this study, an adapted SV index is proposed that considers the nature of the hazard – marginal flooding in an estuarine context under storm surge conditions – in the Tagus river estuary. The methodology and first results of the SV assessment are presented and discussed. The study is integrated in the research project “MOLINES - Modeling floods in estuaries: from the hazard to the critical management” whose objectives include (i) the improvement on the knowledge about flooding processes under storm surge processes, combined with tide effect and urban drainage for different climate scenarios, (ii) the assessment of exposed elements, vulnerability and risk (iii) and the definition of a coordinated strategy for flood risk management.

The Tagus estuary is located in Portugal, covering partially 11 municipalities, including the capital, Lisbon, and its metropolitan area (Fig. 1). Along with the relevance of social and economic exchanges within and between margins, the study area is also sensitive in terms of densely urbanized areas, exposure of critical and sensitive infrastructures, and of its ecological functions with part of its upstream area legally protected as a natural reserve [7].



**Fig. 1.** Geographical context of the study area. Source: Land Use Map 2007 [8]; estuarine and tide data provided by Prof. Paula Freire [9].

After a description of the methodological procedures that conducted to the final social vulnerability index, the paper presents the results, stressing the relevance of analyzing each of the components of SV separately, and discusses the major challenges derived from the adopted geographical unit of analysis.

## 2 Methodology

### 2.1 Set the scope

The definition of the inundation and the socioeconomic contexts set the scope for the SV assessment (Fig. 2), which followed the methodology proposed in the definition of the social vulnerability index (SoVI<sup>®</sup>) [2]. This methodology is widely applied in several geographical contexts and at different scales. Scale constitutes, in fact, a challenging factor in our study given the local and geographically narrow context that an estuarine area represents. Being one of the first steps of the process, the selection of the geographical unit consisted therefore in a sensitive and crucial task, which would depend on the extension of the flooded area as well as on the socioeconomic characterization.

An inundation model for the estuarine area was set up for several probabilistic return periods for both present and future mean sea levels. Extreme water levels in the estuary were determined following the approach of [10], whereby measured sea levels at a nearby coastal station (Cascais, cf. Fig. 1) were statistically analyzed to determine synthetic time series associated with specific return periods (20, 100 and 1000 years). Those time series were then used to force a circulation model, which describes the hydrodynamics (velocities and water elevations), in the estuary [11].

The characterization of the socioeconomic dynamics of the estuary's margins recurred to the analysis of the demographic dynamics, analysis of mobility and commuting from home to school and workplace, with particular emphasis on fluvial transportation between left and right margins and an analysis of potentially affected functions in the case of a disaster (elder and childhood infrastructures, commercial and industrial facilities, civil protection bodies).

The understanding of the inundation model and the socioeconomic dynamics constituted intermediate results that are not the object of this paper, although they led to the necessity of an approach of the estuary in a broader sense, not limited to the hydrologic dimension. Thus, our concept of estuarine area encompasses the estuary biophysical and the human dimensions, which means that the boundary of the study area extends beyond the limit of the highest astronomical tide line [12], to incorporate also the socioeconomic relations that take place along and between estuarine margins.

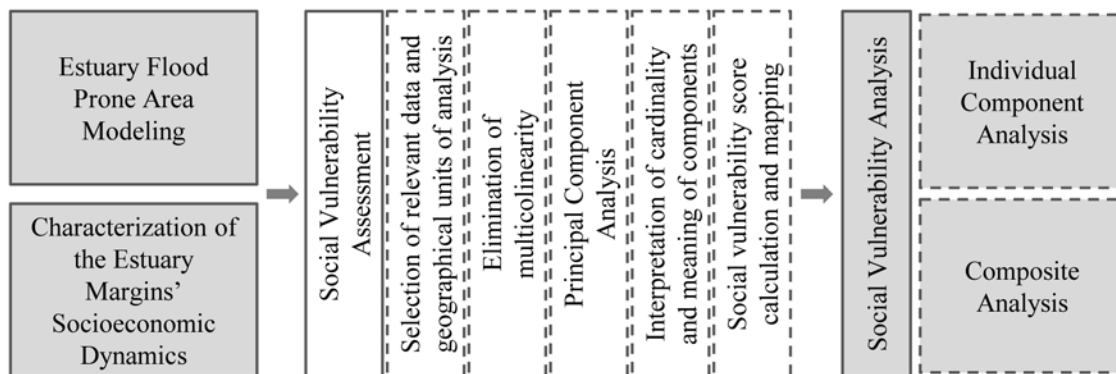


Fig. 2. Framework of the social vulnerability assessment

### 2.2 Social vulnerability assessment

Using a broader concept of estuarine area affected in the definition of the study area and the selection of the units of analysis for the SV assessment. Both processes are interdependent since the number of units of analy-

sis – the SV assessment is based in Principal Component Analysis (PCA) thus requiring a balance between the number of units and the number of SV related variables – would depend on the dimension of the study area. The options for units of analysis were: the parish (or commune, “freguesia” in Portuguese), the statistical block (SB) and the sub-statistical block (S-SB).

The definition of the study area was supported by the combined application of distinct criteria: (1) framing fluvial geomorphology led to the exclusion of areas upstream of the estuary or located in the sea shore; (2) from the resulting area, units within a buffer of 1000 meters from the highest astronomical tide line were included; (3) as well as those with more than 20% of the area under 10 meters height (a value above the maximum depth provided by de inundation model); (4) finally, urban connectivity was accounted for in order to avoid both the exclusion of relevant urbanized areas and the existence of enclaves.

The geographical units that fulfilled those criteria are summarized in Table 1. Considering the optimal relation between the interpretative capacity provided by the mean area, and the minimum number of units necessary to allow the application of the SV model, the statistical block was selected. In fact, the number of parishes is too low to perform PCA considering that previous SV assessments – both from the authors and as well as those presented in the scientific literature (e.g., [1, 6, 13]) – normally recur to between 20 and 40 variables, while the number of S-SB is adequate for PCA but the interpretative capacity is reduced because of the high heterogeneity and dispersion of areas. For example, frequently a sub-statistical block can consist of a roundabout or of a single building. However, S-SB will be used in further steps of the MOLINES project regarding local risk assessments to take place in two selected sites. In summary, the combined application of the above criteria resulted in the selection of 1147 statistical blocks with a mean area of 0.58 km<sup>2</sup>.

Statistical blocks are delimited by the water level in the vertical datum (Mean Sea Level) in the estuarine side. In our study, we opted for considering as inland only the areas above the highest astronomical tide line which required the clipping of SB polygons between this limit and the water level limit.

**Table 1.** Options for units of analysis in SV assessment and their distribution by municipality. Source: BGRI [14].

Municipalities	Area (km <sup>2</sup> )	Parishes		Blocks		Sub-blocks	
		No.	Mean area (km <sup>2</sup> )	No.	Mean area (km <sup>2</sup> )	No.	Mean area (km <sup>2</sup> )
Alcochete	88.37	3	29.46	27	3.27	311	0.28
Almada	17.09	8	2.14	118	0.14	492	0.03
Barreiro	21.66	8	2.71	113	0.19	626	0.03
Benavente	291.88	1	291.88	2	145.94	31	9.42
Lisboa	19.49	31	0.63	266	0.07	1239	0.02
Loures	33.13	12	2.76	116	0.29	969	0.03
Moita	19.56	6	3.26	86	0.23	523	0.04
Montijo	34.19	4	8.55	52	0.66	695	0.05
Oeiras	12.34	6	2.06	119	0.10	669	0.02
Seixal	28.37	5	5.67	144	0.20	681	0.04
V. F. Xira	104.32	8	13.04	104	1.00	763	0.14
<b>Total study area</b>	<b>670.39</b>	<b>92</b>	<b>7.29</b>	<b>1147</b>	<b>0.58</b>	<b>6999</b>	<b>0.10</b>

The selection of variables is the next step in SV assessments. The more dimensions of SV are represented the more accurate and holistic will the understanding of vulnerability location, sources and processes be. In our study, an initial set of 126 variables was considered. Table 2 describes the source, the geographical aggregation level, the dimension of SV represented and the number of initial input variables by source. Most variables are provided by the 2011 Population Census, performed by the National Statistics Institute (INE).

**Table 2.** Characteristics of the initial 126 input variables considered in the SV assessment

Source	Aggregation	Dimension of SV represented by the variables	No.
Population Census	Sub-statistical block	Age, gender, education, housing, employment, economic power, mobility and commutation	76
Population Census	Parish	Particular features of SV dimensions (mobility and commutation, persons with special needs, immigration, housing accessibility, homeless,	27
Social Chart	Parish	Child, youth, adult and community social support (no. of beneficiaries and equipments)	9
Official mapping institute	Polygonal	Land use	7
Civil protection national authority	Point, linear and polygonal data	Educational, health, transportation, civil protection, road network and elderly equipments and infrastructures	6
Fluvial transport company	Point data	Passengers between fluvial stations	1

Table 2 shows that some particular and relevant dimensions of social vulnerability – immigration, homeless persons and persons with special needs, among others – are only represented at the parish level. In such cases, the value that the parish presents was applied to all the SB inside its limits. The following steps of the social vulnerability assessment are (Fig. 2): (1) data collection and integration; (2) normalization of variables to the z-score; (3) test of multicollinearity between input variables; (4) execution of Principal Component Analysis (PCA); (5) interpretation of component groups and attribution of their cardinality, according to their role in explaining SV; (6) sum of component scores without weighting; (7) linear transformation of values to an interval between 0 and 1; (8) cartographic representation of the score of each statistical block according to the standard deviation (SD).

Regarding the third step, several methods are applied to the 126 initial variables in order to select the most robust ones. The first method consists of calculating the Pearson coefficient's correlation between all the pairs of variables, deciding upon which of the variable in the pairs that present a correlation higher than 0.7 is more relevant and easily interpreted in terms of SV. A typical example is the strong correlation between the ageing index and the percentage of people over 65 years old, where the latter is usually preferred. Also, the variables that present a communality extraction value<sup>1</sup> below 0.6 are disregarded. These operations are iteratively executed and the general robustness of the set of data – and its suitability to PCA – is monitored through the verification of the Kaiser-Meyer-Olkin (KMO) measure which must be higher than 0.8 so it can be classified as “good” [15].

The fifth step is the one requiring the more interpretative capacity. The name of the component is attributed considering the variables with load superior to 0.5 or inferior to -0.5 – generally, two to six variables in each component. The signals of these same variables also allow defining the cardinality of the component, which is important to verify if the score in each geographical unit is in accordance with the sign of the component. For example, if the variable “% of population with higher education” presents a positive loading in a given component, the score of all SB in that component must be inverted so that high percentages of population with higher education can correspond to low levels of SV. Following an iterative application of steps (3) to (5), 34 variables were selected to which the steps (4) to (8) were performed.

The sixth step is an assumption made from the beginning by the authors who developed the SoVI<sup>®</sup> [2] and followed since then in other researches (e.g. [16]). In fact, despite the different percentage of variance explained by each component, one cannot assume that components should be weighted unevenly. The linear transformation performed in the seventh step was introduced in the model presented in [11] because, albeit the fact that *z-scores* are used thus presenting a mean value equal to zero, the range of values between components

<sup>1</sup> A communality value of 0.6 means that 60% of the variable's variance is being explained by the number of extracted components. Following the SoVI<sup>®</sup> methodology, an Eigenvalue of 1 is adopted in order to extract the principal components.

differs significantly. Therefore, the transformation would allow for an easier comparison between the scores. The outputs consist in cartographic and tabular data for each of the variables considered as initial input data, each of the PCA components and for the composite SV index.

### 3 Results

Beginning with an initial set of 126 variables, PCA was performed with 34 (Table 3), all of them with communality extraction higher to 0.6, and a resulting KMO measure of 0.813. Initially, 76 and 27 variables were extracted from Census data at the SB and parish levels, respectively (cf. Table 2). From the 34 final variables, 22 come from the Census data at the SB level and 8 at the parish level. One can conclude that a ratio of 2.82 and 2.75 was obtained respectively for the relation between initial and final Census derived variables at both levels, which may indicate that the decision of including specific and complementary variables at the parish level was positive, and did not undermine the robustness of the set of data.

**Table 3.** The 34 variables used in the social vulnerability assessment in the Tagus estuary.

Code	Description (unit)
Ed_ne_repa	Buildings needing repair (%)
Desl_auto	Resident population that uses car as a regular means of transport (%)
Fam_unipe	Housing units with only one member (%)
Pop_1_difi	Resident population with at least one difficulty (%)
Ed_ate1919	Buildings built before 1919 (%)
AlojArrend	Renter-occupied housing units (%)
Fam_monopa	Monoparental families (%)
Ed_1971a11	Buildings built between 1971 and 2011 (%)
Pop_15_24	Resident population between 15 and 24 years old (%)
Fa_c_5mais	Families with 5 or more members (%)
In_freq_sec	Resident population attending secondary school (%)
Fa_dim_med	Mean family size (no. of individuals)
In_est_mun	Resident population attending secondary education in the municipality of residence (%)
Almais200m	Housing units with an area higher than 200 m <sup>2</sup> (%)
In_sup_co	Resident population with higher education completed (%)
Al_50_100m	Housing units with an area between 50 m <sup>2</sup> and 100 m <sup>2</sup> (%)
Al_5maisDi	Housing units with 5 or more rooms (%)
In_3bas_co	Resident population with 3rd. cycle of primary education completed (%)
Mov_pend	Mean duration of commutation time (min)
SecUsaBarco	Employed or studying resident population that potentially uses fluvial transportation (%)
Ed_pre_esc	Resident population between 3 and 5 years old attending pre-primary education (%)
In_et_mun	Resident population studying or working in the municipality of residence (%)
Ed_3mais_a	Buildings built structurally to have 3 or more housing units (%)
Ed_5mai_pi	Buildings with 5 or more floors (%)
Piso_ed	Floors by building (no. of floors)
Ed_91a2011	Buildings built between 1991 and 2011 (%)
Pop_65mais	Resident population over 65 years old (%)
Al_s_estac	Housing units without parking place (%)
In_sec_co	Resident population with secondary education completed (%)
In_nao_ler	Illiterate resident population (%)
DensRV	Road network density (km/km <sup>2</sup> )
DensPop	Population density (no. of residents/km <sup>2</sup> )
Ed_km2	Building density (no. of buildings/km <sup>2</sup> )
Res_5_mun	Resident population who 5 years before lived in another municipality (%)

Cutting the explicative components at an Eigenvalue of 1.05, a total of eight components is obtained that explain 75.1% of the total variance (Table 4).

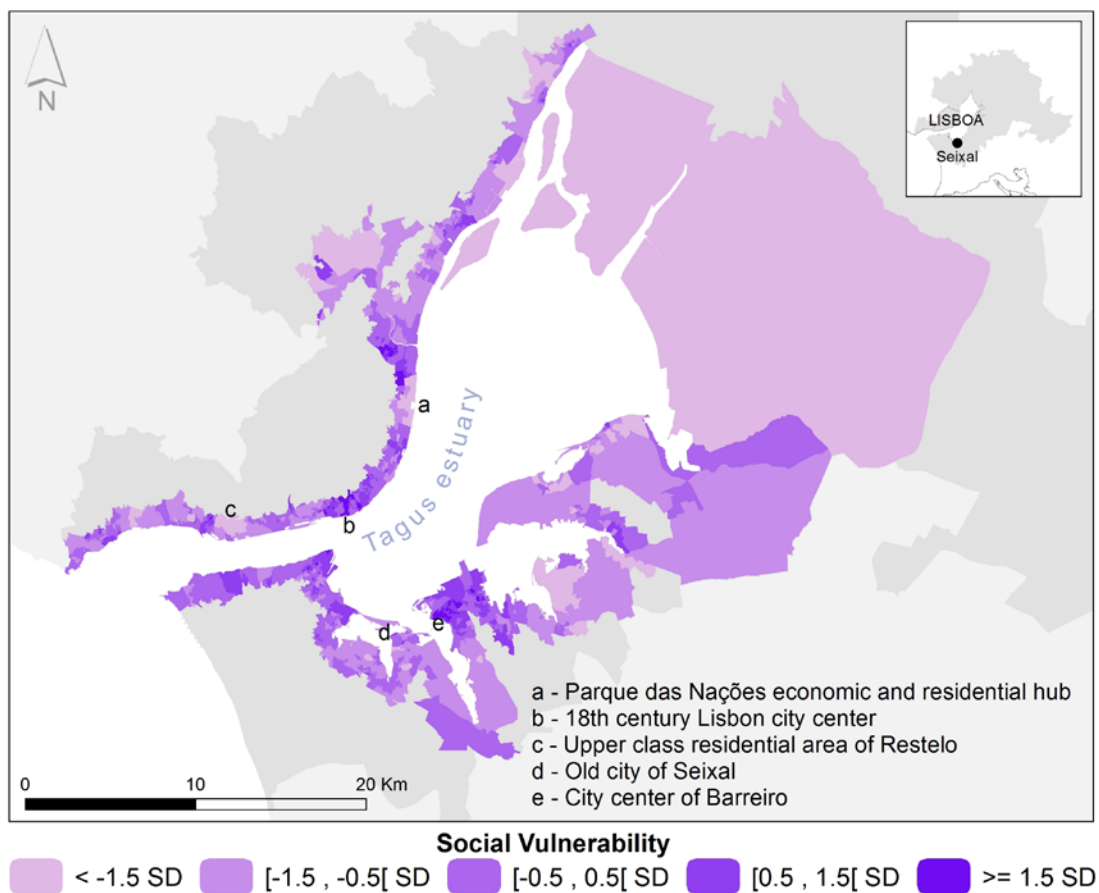
**Table 4.** Principal components of social vulnerability in the Tagus estuary.

Component (% variance explained)	Signal	No. of variables	Explicative variables (loading > 0.5)
Degraded urban context with potentially conditioned population (21.9)	+	9	Buildings needing repair (.820) Resident population that uses car as a regular means of transport (-.778) Housing units with only one member (.699) Resident population with at least one difficulty (.667) Buildings built before 1919 (.613) Renter-occupied housing units (.543) Single parent families (.534) Buildings built between 1971 and 2011 (-.504) Resident population studying or working in the municipality of residence (.563)
Residential urban context of families with small and young children (15.7)	-	6	Resident population between 15 and 24 years old (.865) Families with 5 or more members (.753) Resident population attending secondary school (.737) Mean family size (.681) Resident population attending secondary education in the municipality of residence (.659) Resident population over 65 years old (-.537)
Residential context of population with high purchasing power (10.5)	-	6	Housing units with an area higher than 200 m <sup>2</sup> (.796) Resident population with higher education completed (.696) Housing units with an area between 50 m <sup>2</sup> and 100 m <sup>2</sup> (-.676) Housing units with 5 or more rooms (.650) Resident population with 3rd. cycle of primary education completed (-.570) Housing units without parking place (-.596)
Population's mobility (9.2)	-	4	Mean duration of commutation time (-.840) Employed or studying resident population that potentially uses fluvial transportation (-.799) Resident population between 3 and 5 years old attending pre-primary education (.684) Resident population studying or working in the municipality of residence (.600)
Tall buildings and high density of households (6.5)	+	3	Buildings built structurally to have 3 or more housing units (.810) Buildings with 5 or more floors (.783) Floors by building (.772)
Old buildings with aged population (4.2)	+	3	Buildings built between 1991 and 2011 (-.778) Resident population over 65 years old (.674) Housing units without parking place (.609)
Educational level of the population (3.9)	-	2	Resident population with secondary education completed (.818) Illiterate resident population (-.780)
Population density (3.2)	+	3	Road network density (.823) Population density (.766) Building density (.766)

The components extracted from the PCA analysis express diverse dimensions of SV such as population age, socioeconomic status, education, employment, mobility and commuting, urban typology, housing conditions, family structure and special needs populations. Indeed, complementarily to the analysis of the composite SV index, the isolated analysis of each component provides a relevant understanding of the factors influencing and differentiating SV geographical patterns [1].

In our study, the first four components explain 57.3% of the total variance and refer to: 1 – elder population living in old buildings, 2 – large families, 3 – population with high economic power and qualifications, 4 – commuting and mobility from home to workplace or school.

Relative frequencies of SV classes show that 7.7% of the statistical blocks present very high social vulnerability, 21.2% present high, 40.3% present moderate, 24.9% present low and 5.9% present very low social vulnerability. Population density is not a differentiating factor as equally highly populated settlements are classified in both extremes of the classification scale. Older constructions and their respective residents seem to be associated with higher SV, as well as areas located near fluvial transportation interfaces.



**Fig. 3.** Social vulnerability for the Tagus estuary

Areas **a** to **e** in Fig. 3 illustrate local urban zones where the SV classification was analyzed along with the expert knowledge on the demographic and socioeconomic contexts of these areas. Place **a** (Parque das Nações) refers to a vibrant and dynamic cultural, residential and economic hub, with new buildings, high economic power families and high density lifelines and support infrastructures, resulting in “very low” SV. Place **b** represents generically the so-called “Baixa Pombalina” – after the name of the Marquis of Pombal who coordinated the rebuilding of this downtown area after the 1755 Lisbon Earthquake – which is still a vital zone in terms of economic, administrative and political activity, although old buildings, aged population and the



concentration of fluvial, metro, train and road interfaces make this area “highly” and “very highly” vulnerable, particularly to disruptions caused by flooding. Place **c** (Restelo) refers to a low urban density area, with single-family houses occupied by high-income families, several of these houses corresponding to embassies, resulting in “very low” SV. Place **d** corresponds to the Seixal old city center, one of the local case studies to be assessed in more detail in the next work packages of the project (cf. Figure 4). Place **e** corresponds to the “Barreiro” built-up area center. This area is marked by highly populated SB, from the middle and lower social classes which depend greatly on fluvial transportation for the daily commutation to the work places on the other margin of the river. This urban area is also characterized by high unemployment rates and aged population, which concurs to the classification of “high” and “very high” SV.

Future work will focus on local study areas, one of them located in the Seixal Bay (Fig. 4). For this study area inundation models exist considering 20, 100 and 1000 year return periods, accounting for an estimated sea level rise of 1.5 meters. In the Seixal Bay no SB classified with “very high” SV is present, although some margins of relevant built-up areas – Seixal, Amora and Laranjeiro – are classified with “high” SV (Fig. 4). The figure also illustrates as a SLR of 1.5 meters represents a significant increase in the flooded area in some near-shore areas. For the 100-year return period, the SLR scenario would double the flooded area, from 0.78 km<sup>2</sup> to 1.55 km<sup>2</sup>.

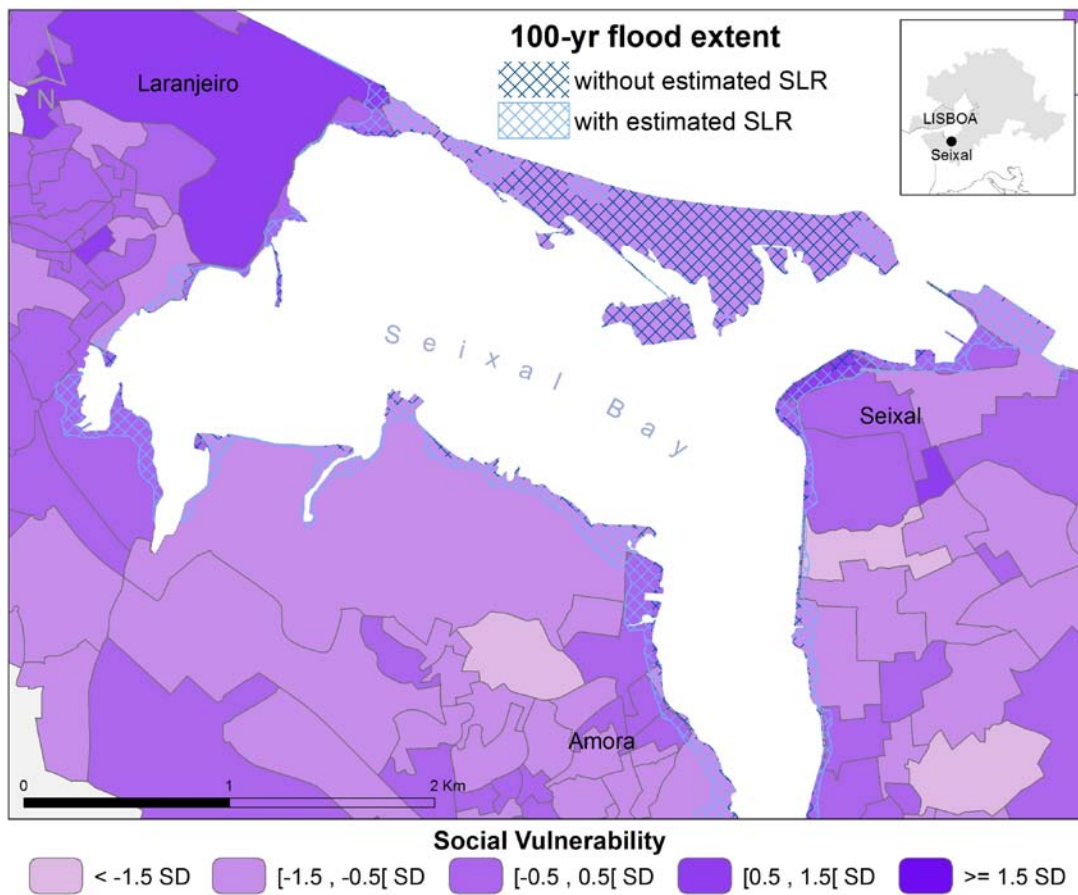


Fig. 4. Social vulnerability in the Seixal Bay area and flooding scenarios.

## 4 Discussion and final remarks

Risk governance strategies should adopt the major objective of promoting a durable reduction in vulnerability. Assessment – as one of the pillars of risk governance – is key to the understanding of hazards, the contexts where they can occur, and the potential for loss, thus concurring to the adoption of the most efficient and adequate risk management strategies. A balance between conceptual comprehensiveness and geographical detail is required so that social vulnerability assessments can be effective tools in risk management.

The adoption of a local scale posed some methodological challenges, together with the focus on a specific hazard. Both - the use of the statistical block as the geographical unit of analysis and the focus on flooding in estuaries - required a thorough effort in finding the most adequate and pertinent data, and later, in the interpretation of the results. In fact, the majority of existing studies focus on larger scales such as the region, the municipality and the parish. Previous SV assessments at the municipal level, for instance, are based on variables that can only be interpreted at that scale of analysis. For example, the variable “percentage of the population served by water treatment facilities” can in fact be used to differentiate the municipalities’ vulnerability in terms of the water quality that is supplied to the population. The values of that variable are meaningful at that administrative level. Nevertheless, this variable can’t be used to differentiate SV at the statistical block. In fact, the presence or proximity of such facility in a given SB can play the opposite role, i.e., to be representative of lower environmental quality – due to noise, smell, landscape degradation, etc. – and thus of higher vulnerability. This same conclusion can be extended to other variables normally used in SV assessments.

A previous application of the SV assessment methodology developed in the CES, for the Central Portugal region, using regional and local geographical units of analysis resulted in the identification of local characteristics that can be the basis for specific risk planning strategies [17]. A research on the socioeconomic vulnerability to flooding in the coastal area of Germany concluded that, regarding the potential economic impacts, risk evaluations result in higher values when assessed at the micro-scale then at the meso-scale and national scale [18], which suggests that the accuracy of assessments is scale-dependent.

On the perspective of data availability, a high number and diversity of variables widely used in the SV literature are available at the municipal scale, but are scarce at the statistical block level (e.g., cash withdrawal at ATM, purchase power, municipal expenses with health, environment and civil protection). Independently of these constraints, and given the fact of assessing social vulnerability at the local level, the results obtained so far show that the selection of the SB as the unit of analysis proved to be advantageous. Such unit of analysis made it possible to distinguish variations in SV between contiguous neighborhoods and even groups of buildings. The differences highlighted were verified and confirmed with the support of local municipal technicians who have a thorough knowledge of the socioeconomic and biophysical landscape. Regarding the availability of data sources, this study highlights the relevance and irreplaceable function of the Census data provided by the Statistics Portugal institute (INE).

The nature of the hazard – flooding in an estuarine context with the effect of storm surge and urban drainage – stimulated us to identify specific variables that could be representative of vulnerability dimensions related to commutation, highlighting the relevance of the Tagus estuary as a connectivity resource. A regional study with a strong focus on local details such as the one presented herein provided a good identification of social vulnerability drivers in the Tagus estuary. The wide perspective of vulnerability provided by the eight SV components was only made possible by the quality and diversity of input data.

Social vulnerability assessments come in accordance with the need for long-term estuarine flood risk management strategies which focus on mitigation and adaptation to the adverse effects of flood hazards. Considering urban and demographic dynamics as drivers of flood damage patterns [19](Santos et al., 2014), social vulnerability assessments constitute relevant tools that allow predicting the degree of the impact and the communities’ capacity to resist and recover from disasters.

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