



# Social vulnerability and coastal hazards: Acknowledging floating population needs in Barcelona, Spain

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Abstract: Increasing occurrences of flash flooding poses significant social and economic threats to Barcelona. Approximately 65% of the population reside along the coast. Many rely on beach assets to attract 35 million annual visitors that buttress the city's 7.1 billion EUR tourist sector. Both residents and tourists are vulnerable to late-summer and early-autumnal flash floods of intense rainfall events that that exceed the capacity of urban drainage systems designed for 55% less loading. Government efforts do not account for non-resident population needs by focusing primarily on residents' safety following floods. Regular flash floods in Barcelona indicates an urgent need to develop a water sensitive strategy that comprehensively accounts for point source pollution in this vulnerable coastal region, as well as for its socioeconomic profile. While Social Vulnerability Indices have been developed for climate change-related disasters over the past fifteen years, these indices are designed for use at a national scale and overlook the needs of seasonal residents (e.g. short-term residents and tourists) in social profiling. This research broadens the scope of social vulnerability indices to factor in temporary resident needs in disaster planning at a regional scale. The social vulnerability index can help government planners include floating population groups in postdisaster management efforts.

**Keywords:** Social vulnerability index; SVI; resilience; seasonal population; disaster risk reduction.

#### 1. Introduction

Coastal metropolises are sensitive to hazards due to their having high concentrations of people and economic activities within their geographic boundaries (Guillard-Gonçalves et al., 2015). Previous climate change research has indicated that densely populated coastal areas are vulnerable to disasters such as flash floods (Velasco et al., 2018). Consequently, preparing for and minimizing vulnerability to hazards such as urban flooding is of interest to coastal cities. Social vulnerability (SV) is a population's inability to cope with adverse impacts of natural and/or man-made disasters. It encompasses characteristics that influence human susceptibility to disasters and their ability to respond, as well as context-specific social and environmental factors (such as urbanization and economic activities) (Cutter et al., 2003).

This case study focuses on the second most populous region in Spain (Barcelona). Approximately 65% of its population reside along the coast (idescat, 2018). Increasing occurrences of flash flooding pose significant socioeconomic threats to the province and its residents, as many rely on beach assets to attract 35 million annual visitors that buttress Barcelona's 7.1 billion EUR tourist sector (WTTC, 2017). Both residents and tourists are vulnerable to late-summer and early-autumnal flash floods of intense rainfall events that exceed the capacity of drainage systems designed for 55% less loading (Santos and Martos, 2009).

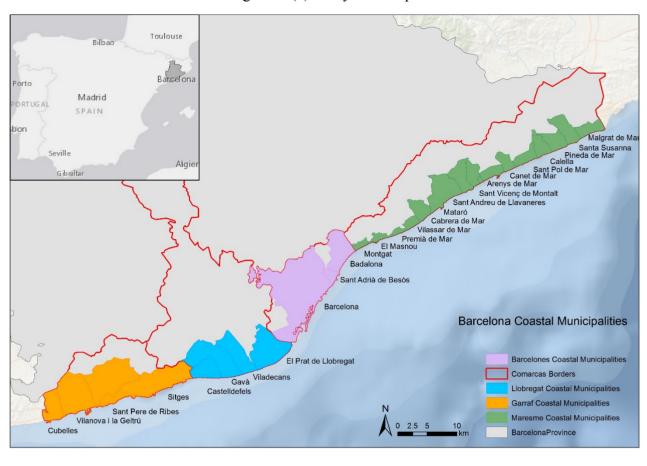
This research follows in the tradition of SV exposure and resilience studies undertaken by Cutter, *et al.* (2003). As per previous research, we analyze available socioeconomic and demographic data to construct a Social Vulnerability Index (SVI) for Barcelona's coastal hazards to link the attributes that make people vulnerable to the support structures and facilities that can help them resist and recover (Gomes, 2018). We, however, diverge from Cutter, *et al.* (2003) in that we use municipal-level data instead of country-level data to develop an index that takes into account Barcelona's short-term residential and tourist population as vulnerable groups, as this floating population (*població estacional*) has thus far been overlooked in previous SVIs. Tourists especially are important to account for because Barcelona's tourist numbers increased by over 25% between 2008-2015 (Barcelona City Council, 2015).

The study's aim is to inform the development of floating population variables. Developing means to assess this SV can facilitate our understanding of factors that make non-residents and places susceptible to disasters over time and in different places. It additionally can offer guidance to government officials responsible for prioritizing resources in emergency events (CDC, 2018) – especially in areas that are heavily reliant on tourism.

## 2. Study Area & methodology

The study area covers coastal municipalities of Barcelona Province (41N, 2.1E UTM coordinates). The coastline is approximately 160 kilometres in length and is relatively narrow with a high elevation. It comprises of 103 beaches distributed along four coastal administrative units (*comarcas*: Maresme, Barcelonès, Llobregat and Garraf) (Figure 1). According to idescat (2018), 5.5 million people reside in these coastal *comarcas*.

Figure 1. (a) Study area map



## (b) Created in Arc GIS 10.5.1 (1)

We examined both residential and floating populations' SV to coastal hazards in 25 municipalities located within these four *comarcas*. (We excluded a further 3 municipalities with <5,000 inhabitants due to their having unreliable data.) Data is limited to the 25 municipalities due to the study's coastal hazards objective. In this study, we applied the US Federal Emergency Management Agency's SV tool using R scripts to prepare and analyze data (FEMAdata, 2016; R Development Core Team, 2008).

### 2.1 Data collection and preparation

Table 1 summarizes the variables used for analysis. The first 28 variables are based on SVI research from Cutter et al. (2003) and Guillard-Goncalves et al. (2014) and Martin et al.'s (2017) adaptations for European contexts. Variables development accounted for European contexts – such as foreign nationals living in Spain, as Guillard-Goncalves et al. (2014) noted that ethnicity components are not included in the Cutter framework. The latter 5 floating population variables are drawn from Barcelona's latest municipal (2011) census (idescat, 2018). Barcelona's statistics institution (idescat) includes in its floating population those who have a primary or secondary municipal residence; tourists who stay overnight at tourism establishments; and students or workers who travel between municipalities but do not stay overnight. Idescat (2016) bases floating population figures on censuses and tourism, labor, education and lifestyle statistics. We grouped the 33 variables in 11 categories to reflect socioeconomic attributes or support structures: housing and installations, age, race and ethnicity, education, family structure, urban, socioeconomic status, medical services, special needs population, population growth, and floating population.

Code Name	Description						
Housing and services							
PriWatSup   Proportion of dwellings with private water supply/Total dwellings							
NoWatSup							
NoHeat	Proportion of dwellings with no water Supply/Total dwellings						
NoPhone	Proportion of dwellings with no heating/Total dwellingsProportion of dwellings with no telephone line/Total dwellings						
NoBath	Proportion of dwellings with no toilet, bathroom or shower inside the						
NoDatii	apartment/Total dwellings						
NoCool	Proportion of dwellings with no cooling/Total dwellings						
Age	roportion of dwennings with no coornig/rotar dwennings						
Elderly	Population 65 and older/ Population 15–64 years						
-	Population under 15 / Population 15–64 year						
Young	ropulation under 157 ropulation 15–04 year						
<i>Race and ethnicity</i> Spanish	Proportion of population with Spanish Nationality/Total Resident Population						
Foreign	Proportion of population with Spanish Nationality/Total Resident Population Proportion of population with Foreign Nationality/Total Resident Population						
	roportion of population with Poreign Nationality/Total Resident Population						
<b>Education</b>	Droportion of poople elementary school graduates / Total guarder of are but a						
Element Univer	Proportion of people elementary school graduates/Total number of graduates						
	Proportion of population who completed College/Total number of graduations						
Familial structure							
MothersAlone	Proportion of mothers alone with child/total number of families						
ParentsAlone	Proportion of parents alone with child/total number of families						
HouseholdSize	Average number of people per household						
Urban							
Density	Number of people/area (in km <sup>2</sup> )						
Socioeconomic statu	IS						
GDP	Income per capita (thousands of Euros)						
RatUnemLabor	Ratio of unemployed population and labor force						
Act.Rate	Rate of activity						
Agri	Proportion of population employed in agriculture/Active population						
Tou	Proportion of population employed in tourism/Active population						
Renters	Proportion of rented or sub-rented conventional dwellings/Total Dwellings						
Medical services							
Phar	Number of pharmacies for 1000 inhabitants (in 2002)						
HosBeds	Number of hospital beds for 1000 inhabitants (in 2002)						
Special needs popul							
Disabled	Proportion of disabled persons (auditory, visual, motor or mental)						
DisabledDep	Proportion of persons that are disabled and are under 4 or above 65 years old						
Disabl60	Proportion of persons with a disability degree above 60%						
Population growth							
NetMigra	Net Migration (annual average) (rate per 1.000 inhabitants). 2001-2011						
Floating population							
BedHotCamp	Number of beds in hotels & camping						
NonResPop	Non-resident population						
TouEst	Estimated number of tourists results for the period 2002-2015						
RatPopVicandRes	Floating estimates for the period 2002-2015/ resident population						
nonres Res	Non Resident Population Tourist/Resident Population						
	Non Resident i opulation_fourist/Resident i opulation						

Table 1. Variables names and descriptions

To prepare data, we applied a multi-collinearity (Kendall's rank correlation) test to reduce data amplitude because all variables do not have normal distributions. We discarded the Disabl60 variable from the dataset because the Kendall s-b value was below the accepted correlation rate of  $\pm 0.7$ .

## 2.2 PCA with varimax rotation

This is performed to select key principal components (PCs), which facilitates data interpretation. We (1) applied a varimax rotation procedure using the Kaiser Criterion; and (2) normalized the variables with Z-scores. For variables with an eigenvalue higher than one, we excluded those with correlation coefficients <0.4 as they likely do not contribute to SV. We examined the remaining variables by assigning a positive or negative contribution to vulnerability, and considered how socially vulnerable each municipality in the dataset is to coastal hazards.

# 2.3 SVI calculation & GIS visualization

We mapped equally weighted SVI scores in ArcGIS 5.1 using standard deviation classifications of very high to very low vulnerability classes (Figure 2). To note, as per previous SVI frameworks, a positive sign indicates increased vulnerability and a negative sign indicates a diminishing effect (Table 2). We used an absolute value symbol when the variables within the category conflict in contribution. If a component's variables tend to increase SV but have a negative loading (or vice-versa), the component's cardinality is adjusted by multiplying by -1. A SVI is calculated by summing the component values for each municipality (Equation 1).

SVI Score = 
$$PC_1 + PC_2 + PC_3 + PC_4 + |PC_5| - PC_6 + PC_7 - PC_8 + PC_9 + PC_{10}$$
 (1)

## 3. Results

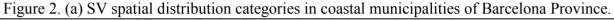
Twenty variables remained after processing, which were clustered according to ten PCs with 87.3% variance. However, we found that three variable combinations (PC3: NoHeat and Disabled; PC7: NoBath and NoCool; PC9: NoWatSup and Agri) have limited relevance to SV in coastal hazard events, and hence excluded these PCs. The variance for the remaining PCs is 66.7% (Table 2).

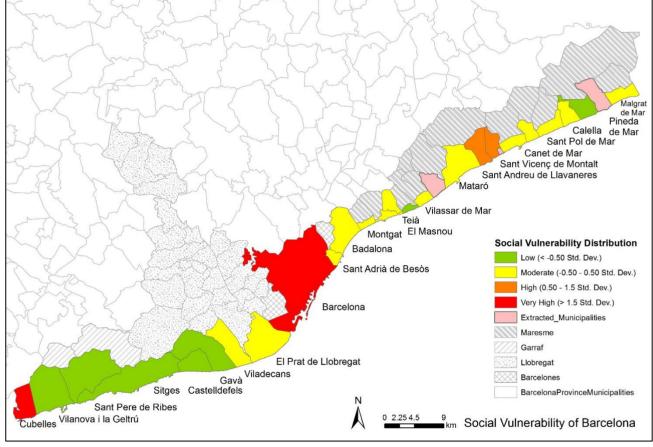
PC	Variance (%)	Vulnerability categories	Sign	Variables	Correlation			
1	26.2	Floating population	+	BedHotCamp	0.439			
				NonResPop	0.449			
				TouEst	0.428			
2	12.6	Housing services & population growth	+	PriWatSup	0.559			
				NoPhone	-0.411			
				NetMigra	-0.403			
4	9.3	Education & socioecon. status	+	Element	-0.468			
4				RatUnemLabor	-0.486			
5	5.9	Race & ethnicity		Spanish	-0.521			
				Foreign	0.472			
6	5.4	Medical services	-	Phar	-0.463			

Table 2. SV components, attributed signs and correlation

8	4.1	Socioeconomic status	-	GDP	-0.567
10	3.2	Age & Familial structure	+	Young	-0.547
				MothersAlone	0.413

After identifying relevant PCs, we mapped the municipalities' SV according to standard deviation distributions of very high (>1.5) to high (1.5 to 0.5), moderate (0.5 to -0.5) or low (<-0.5). Taking into account the SVI score, the most vulnerable municipalities are Barcelona City and Cubelles, while Vilanova i la Geltru, Sitges, Castelldefels, Gava, Teia, Vilassar de Mar, Mataro, Canet de Mar and Pineda de Mar are the least vulnerable (Fig. 2).





(b) Created in Arc GIS 10.5.1

(1)

Both education and socioeconomic status contribute to SV in Barcelona City and Cubelles. Barcelona City seemed to also very vulnerable due to its floating population, whereas wealth was the second contributory factor that affected Cubelles' classification. The nine least vulnerable municipalities did not have any very high PC scores. They additionally each have at least three moderate PC scores, with an overall average score of moderate. Housing services and population growth (PC2) contribute to SV in four of the nine municipalities, whereas sufficient medical services (PC6), wealth (PC8) and/or age/familial structure (PC10) seemed to lower vulnerability.

In terms of the primary contributory factor, the SVI scores indicate that floating populations (PC1) has the highest variance, which suggests that this cluster contributes most amongst the 25 coastal municipalities. Barcelona City is most vulnerable, though it is also a high contributor in four other municipalities (Badolona, Arenys de Mar, Calella and Pineda de Mar). Floating populations are a low

contributor in eight municipalities (Cubelles, Sant Pere de Ribes, Viladecans, Teia, Mataro, Sand Andreu de Llavaneres, Sant Vicenc de Montalt and Sant Pol de Mar).

# 4. Conclusion

This study evaluated the SV of coastal municipalities in Barcelona Province against hazards such as flash floods. We applied the SVI framework to assess which are the most socially vulnerable populations in 25 coastal municipalities. We found that floating populations are the most vulnerable to coastal hazards. This is important to highlight to decision-makers responsible for government disaster risk reduction programs, as this suggests that emergency services should also account for short-term residential and tourist population needs in areas where tourism is a significant economic sector. Using SVI maps can additionally inform how finances and services can be spatially distributed according to risks.

This study joins a body of research that indicates that the SVI framework can inform disaster risk reduction decision-making and prioritization. The findings are also important because the SVI framework presently does not account for non-residential populations in its analysis. This paper thus serves as an opportunity to inform the development of a critical but overlooked variable for contexts that experience high rates of short-term residential and/or tourist populations.

Due to time and resource limitations, we limited the dataset to 25 Barcelona municipalities. We plan to expand this analysis across coastal municipalities in Catalonia to build a more statistically robust index for this region. And while determining and mapping SV factors have the potential to improve disaster response processes, its wider adoption is dependent on there being reliable government data and public institutions having basic statistical analysis knowledge in order to integrate and map statistical and spatial data.

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# **Conflict of Interest**

The authors declare no conflict of interest.

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