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Vulnerability to urban flooding assessed based on spatial demographic, socio-economic and infrastructure inequalities

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ABSTRACT

Urban flooding is a priority in natural risk management and mitigation because it is the most frequent natural disaster in densely urbanised environments. This research explores flood vulnerability in cities by developing an index that can be easily implemented across the world. Our methodology is based on the arrangement of a series variables into three different classes (demography, socioeconomics and infrastructure) and the determination of their spatial variability through a Principal Component Analysis (PCA). We tested the proposed approach in the city of Santander (Spain) where a vulnerability index map was generated based on the combination of the proposed classes. The analysis show that we can reduce complexity from an initially identified 159 relevant variables to 16 representative and impactful variables in terms of spatial variance. Classification of the variables into three different classes made it possible to quantify the main causes of vulnerability to flooding across space. We produce a flood risk map by integrating our findings with a flood hazard map for the same area. This flood risk map gives urban planners detailed information about the most affected areas and allows them to design measures that mitigate the severity and effects of floods optimising available resources.

1. Introduction

Floods were the most frequent natural disaster worldwide in 2020 [1], a trend that will further increase due to climate change [2]. Population growth and urban sprawl [3] are a combined hazard with especially destructive effects, as the consequences of floods are particularly adverse in cities due to their high imperviousness [4,5]. Floods resulted in global economic losses of $105 billion in 2021 [6].

Along with hazard, vulnerability is one of the main components to be concerned with in environmental risk analysis [7]. Socio-economic changes and global migration increase inequalities [8] and hence the spatial pattern of vulnerability. Addressing these in-

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equalities at city scale is therefore required to improve the sustainability of urban areas as proposed in the Sustainable Development Goal 11 of the United Nations [9].

There are different methods to assess vulnerability. In the curve method, damage curves are created and averaged to quantify damage depending on the magnitude of a flood [10]. Complex simulation models, such as fuzzy interval-stochastic programming or Neural Networks, are used to determine vulnerability based on large databases collected over a long period of time [11,12]. The analysis of vulnerability using indices is one of the most widespread approaches in areas such as ecology, health and technology [13–15]. This index approach, based on calculating a score by weighted aggregation variables that determine the population's spatial difference to a particular hazard, was used in this study.

To select the variables that form these indices, Bucherie et al. [16] explain that subjective knowledge-based information is required. This selection depends on the context of the natural disaster to be assessed, the area to be analysed and the specific vulnerability to be measured. Once the variables are selected, different approaches can be used to quantify the spatial distribution and relative impact of the variables on vulnerability, such as multicriteria decision analysis (MCDA), expert elicitation or statistical methods such as principal component analysis (PCA) [17–22].

Studies presenting vulnerability indices differ methodologically in terms of the size of the study area [23], or the type of vulnerability assessed by the index. They focus on environmental, physical, social, economic variables, or a combination of them [24,25]. Vulnerability indices related to natural disasters tend to focus on socio-economic or demographic vulnerability [26].

For the spatial analysis of vulnerability, geographic information systems (GIS) are used to manage geo-referenced information. A large majority of natural hazard analysis studies employ GIS as a main tool in their approach [27–29]. Spatial analysis of vulnerability indices enables the identification of focus areas in terms of exposure to a hazard [30].

As pointed out by Chan et al. [24], there are environmental, physical, social and eco-economic aspects to consider in assessing vulnerability. However, previous studies have focused exclusively on social and demographic vulnerability. We identified a lack of studies that compile these criteria into a single index and provide a holistic view of the problem. Our study aims to concentrate on assessing aspects of vulnerability that directly affect urban dwellers based on demographics or their social and economic constraints. Furthermore, the infrastructures that provide shelter and services to citizens are also considered because their vulnerability may affect directly or indirectly the normal operation of the city.

To fill this research gap, we propose a method for assessing vulnerability using spatial differences in three categories: demographics, socioeconomics and infrastructure. The proposed approach is based on a novel combination of knowledge from existing literature and numerical methods using correlation analysis and PCA. This article aims to demonstrate how a vulnerability index can be obtained by selecting the most significant variables in terms of spatial differences in each of these three categories. As such, the main result to be obtained was a vulnerability map. Due to its sensitivity as a coastal rainy city, the city of Santander (Spain) was used a case study. To obtain a complete picture of flood risk based on its two main components [31,32], this vulnerability map was combined with a flood hazard map previously produced for the same city [33].

2. Methodology

We used disaggregated data from the 146 census tracts that form the city of Santander. These data were acquired from the Spanish National Statistics Institute (INE) and the government of the region of Cantabria [34–36]. Altogether, 159 variables were collected and organized following classifications of previous studies that were selected based on their number of citations and date of publication. Subsequently, a PCA was used to reduce and analyse the variables, selecting the ones with the greatest spatial variability. We then used a weighted sum to map vulnerability based on these variables. Fig. 1 shows our workflow.

2.1. Location

The research was carried out in the coastal city of Santander (Fig. 2). Located in the north of Spain, it is the capital of the region of Cantabria with a population of 172,221 and an area of 36 km^2. Santander has a mild climate (Cfb) according to the Köppen-Geiger classification [37], with humid conditions for long periods and annual precipitation values around 1200 mm [38]. The orography and geology of the city poses flood risks, particularly in streets running from hills to lowlands with steep slopes [39]. The city is built on predominantly calcarenite limestone with a poorly developed, acidic and regolithic soil, typical for wet areas with steep slopes. This orographic, geological and edaphological situation causes low infiltration rates and, high runoff coefficients even in unpaved areas (see Fig. 3).

In terms of its demographic structure, according to the last census conducted in 2011, Santander has a population composition of 12.7% under 16 years, 66.1% between 16 and 64 years, and 21.2% over 64 years. Economically, annual unemployment rate in the city ranges from 16.8% to 19.1%, and the average income per person for the same year is 10,495 euros. In addition, Santander has important infrastructure for the region, such as a hospital, administrative buildings, two university campuses and an airport located outside the city limits.

2.2. Data collection

We used two databases to create demographic and socioeconomic classifications, selecting data based on their availability at the time of the study. Approximately every 10 years, the INE publishes data on the demographic, cultural, economic and social condition of the inhabitants of Spain [34,40]. Our study is based on the 2011 release of these data, which disaggregates the population by sex, age, education, family characteristics, etc. We furthermore used data on income distribution for the years 2015 and 2016 with the same spatial resolution, also obtained from INE which contain economic information from citizens [35,40]. There were two non-

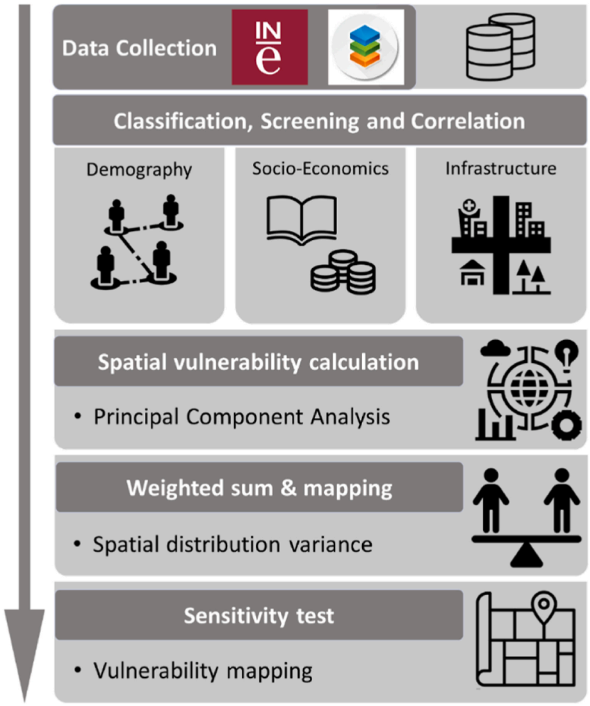

Fig. 1. Diagram flow summarising the steps involved in estimating a vulnerability index.

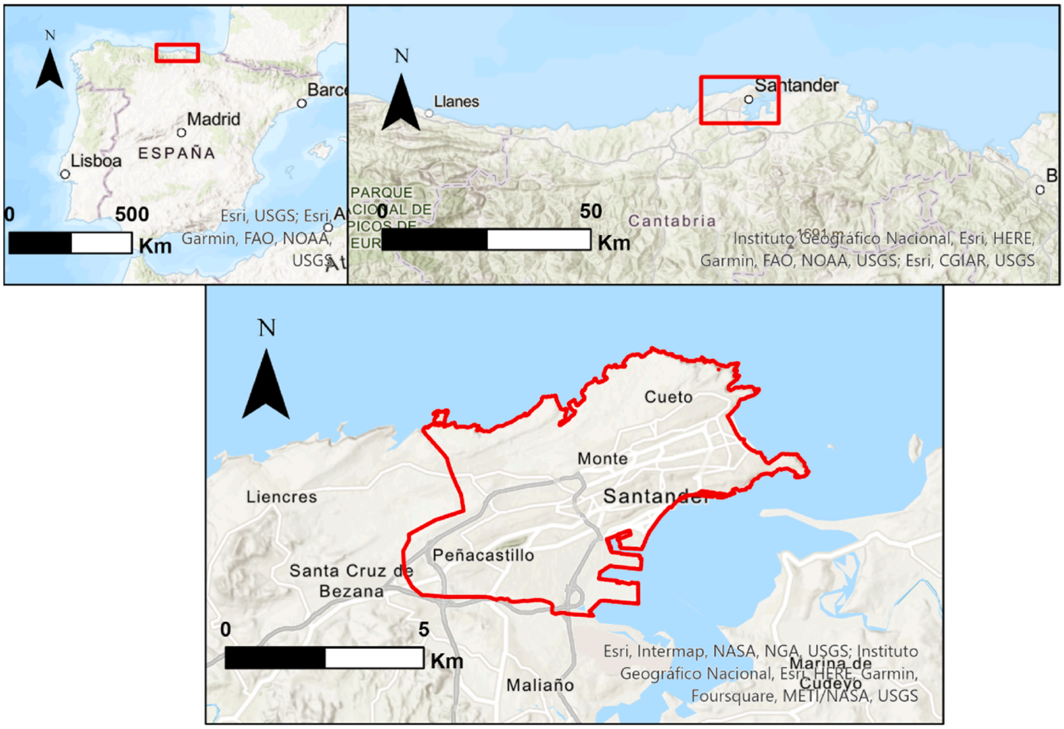

Fig. 2. Location map of the research study area, Santander (Spain).

conformities in the distribution of the census tracts that was solved by merging the respective census tracts. Although slight variations were observed in the values of certain variables over time, the proportion of values across the census tracts is expected to be stable.

Furthermore, we used open access georeferenced data of the most important infrastructure of the city related to health, education, culture and political administration from the government of the region of Cantabria [36]. We cross-checked temporal completeness of the data. All these data (Table 1) were used for the initial screening of variables to determine flood vulnerability of the census tracts.

In the following section, the variables used to calculate vulnerability were chosen using relevant literature on demographic and socio-economic indices [7,41–55]. In parallel, a series of variables related to critical infrastructures that are necessary for the normal functioning of the city and some others that are susceptible to flooding, such as underground parking facilities, was added.

2.3. Classification, screening and correlation

The selected variables were divided into three classes, which were subsequently cross-checked with variables used by other authors for the demographic and socio-economic classes (Table 2). In the case of the infrastructure dimension, no flood vulnerability indices using these variables were found. However, infrastructures are susceptible to flooding (e.g., underground car parks) and can hinder normal operation of the city [56,57].

In order to ensure the reliability and accuracy of our research, we implemented a screening process. This process involved examining the variables utilized in the literature to develop vulnerability indices. Furthermore, we took an additional step to check and verify the soundness of these variables for the case study for further validation [16]. By applying this selection process and incorporating input from both the scientific community and our own experience, we aimed to produce reliable results.

The variables found in the literature were identified from those available in databases. Once identified, variables not relevant to the study and variables that overlapped with others were eliminated. In addition, some of the disaggregated variables, such as different degrees of educational attainment above elementary school level, were joined because their division was not relevant in terms of flood vulnerability.

Table 1
Spanish databases used in the research.

Data	Format	Reference
Demographic and social data	Polygon shapefile	[34,40]
Economic data	Polygon shapefile	[35,40]
Infrastructure	Point shapefile	[36]

Table 2
Initial selected variables from affecting vulnerability to flooding in the city cross-checked with other author organized into three classes.

Class	Code	Description	Related bibliography
Demography	Tot_Pop	Total Population	[41,48,49]
	Density_Pop	Population Density	[41,50,51]
	<16	People under 16 years of age	[48,50,52,53]
	>64	People over 64 years old	[49–55]
	<16 || >64	People under 16 (inclusive) and over 64 (inclusive) years of age	[52,54]
	Non_Spa	Foreigners	[50,54]
	Home = 1	Home with 1 people	[7,50]
	Home>5	Home with 5 people or more	[7,50]
	Prsn_Home	Average Home size	[51,54]
	Mean_age	Average age of the population	[49,54]
Socio-economics	Studies_no	Illiterate people, uneducated and under 16 years of age without mandatory studies	[41,49,51,54]
	Inc_mean_pers	Average net income per person	[42,49,51,52]
	Inc_mean_hgr	Average net income per family	[41,52,55]
	Inc_mean_udc	Median income per consumption unit	[52]
	Inc_median_udc	Median income per consumption unit	[52]
	Poverty_ threshold	Population with income per unit of consumption below 60% of the median	[49,52]
	Non_married	Population that is not married	[43]
	Rent&Mortage	House with payments pending or in rent	[44,49]
	<90sqm	Families that live in houses less than $90m^2$	[45,46]
Infrastructure	Residential	Total Dwellings	[42,44,49]
	House_1st	Dwelling used as a main residence	
	House_2nd	Dwelling used as a secondary residence	
	House_Emp	Empty dwelling	
	Room ≤3	Dwellings with less than 3 bedrooms	
	Room>3	Dwellings with more than 3 bedrooms	
	Health	Health centres/hospitals	[41,54]
	Parking	Underground parking	
	Cult	Museums, Monuments and buildings of cultural interest	
	Educ	Educational facilities	[47]
	Gov	Government facilities	

Then, correlation analysis and a principal component analysis (PCA) were applied to reduce the number of variables to the most impactful and relevant ones [58]. A correlation coefficient of 0.75 was used as a minimum threshold to indicate a strong or very strong relationship between variables [59]. For those which reach the threshold, the logical relationship among them is studied. In case two variables describe the same aspect and group of inhabitants they can be discarded to avoid double-counting.

2.3.1. Demographic classification

Demographic characteristics are major determinants of vulnerability to floods [60]. This class stands for characteristics that explain the structure of communities living in a certain place and time. Structure is understood as the characteristics of population including amount, among age and other. The census carried out by INE defines and delimits the demographic variables, ensuring their clarity and enabling subsequent reasoning. For example, “family” is defined as a group of people who cohabitate a dwelling and are tied by bloodlines or partnership agreements, and compose a single household. A “household” is defined as a group of people residing in a single dwelling, without the need for kinship. A term prone to causing confusion is “foreign person”, referring to people who do not have the Spanish nationality. The relevance of this variable lies in the fact that foreigners may have difficulties in accessing crucial information on warnings and recommendations from local authorities due to language and cultural barriers, limited access to reliable sources of information, lack of awareness of available resources and the reluctance of some foreign residents to seek information on disaster preparedness [61–63]. It is possible for an individual to obtains the Spanish nationality and thus leave the group of foreign people. Also, the code “$<16 \,||\, >64$” (people under 16 and over 64 years of age) was considered to see if it is possible to combine two groups of vulnerable citizens where age is a common variable.

2.3.2. Socio-economic classification

These are conditions of the inhabitants related to the resources they have available to cope with a hazard and reduce its impact. Social resources such as education or interpersonal relationships, and economic resources such as income or home ownership are assessed. Education or economic resources are key variables which are important before, during and after a hazard. Before has to do with streamlining material and personal protection through social interactions that contribute to a better organisation of the population or a better interpretation of security information. During refers to managing resources efficiently. After is about turning back to normality in a short period of time.

Thus, we found variables such as people who cannot read or write or who have not passed primary education that were merged in a single variable to be comparable to previous studies [41,49,51,54]. Same action was taken to aggregate all dwellings smaller than ninety square metres into a single variable. A further variable in this class is the consumer unit; this term is used to make a better comparison of the purchasing wealth of a household. The number of consumer units is calculated using a modified scale of the Organisation for Economic Cooperation and Development (OECD), which gives a weight of 1 to the first adult, a weight of 0.5 to other adults and a weight of 0.3 to children under the age of 14. Once the income per unit of household consumption was calculated, it is allocated equally to each member of the household.

2.3.3. Infrastructure classification

There are buildings or facilities where basic functions are carried out within a city. These include residential buildings where inhabitants live, which serve as flood shelters, and others that are necessary for the normal operation of the city such as health, education or city governance centres. Also, additional infrastructure that could be seriously damaged by flooding, such as underground car parks, was added to this category due to the potential value of the vehicles that could be placed in these facilities.

2.4. Spatial vulnerability calculation

PCA is a statistical procedure to reduce the dimensionality of data to a set of uncorrelated variables called “principal components” which explain the majority of variability found in the original data [64,65]. Each principal component is made up of the original variables' coefficient sums, which change each into a variable that explains a particular percentage of the total variability [66]. These principal components are ordered from highest to lowest importance for variability explanation.

PCA helps identify variables causing variability in the most important principal components which, upon selection, can reduce dimensionality with minimal information loss [67]. Furthermore, this information can be used to define the weight of each variable in order to aggregate them into an index. For this study, we used the sum of the minimum principal components necessary to explain at least 50% of the cumulative variability as a selection criterion.

After identifying the variables that contribute most to the principal components, a critical reasoning based on the PCA biplot was carried out. The purpose of this analysis is to group variables that may have some relationship in their variability and suggest the reasons that can explain this pattern.

2.5. Weighted sum and mapping subindices

Weights for the selected variables in each class were calculated by taking the orthogonal sum of the absolute loadings of each variable in its normalised form within each principal component [68,69]. Specifically, the orthogonal sum was selected due to the uncorrelated contributions of each of the PCA principal components. This equation represents a modified expression of a correlation between a component and a variable based on the loading concept, which sums the variable weights of the same variable from different principal components [65]. The variance coefficient of the principal components was used to give more importance to the variables that had more spatial variability between census tracts. In addition, only variables within each principal component that are above the expected contribution of homogeneous variable importance were included. The weights of the variables were then normalised for each class. These weights were multiplied by normalised values from census tracts to obtain each class subindex map.

$$Variable\ weight = \sqrt{\sum_{i=1}^{n} \left(|x_i| \bullet w_i\right)^2}\ , where \sum w_i = 1 \qquad \text{Equation 1}$$

i : *Principal component dimension*

n : *Nº principal component dimensions*

x : *Variable loading in principal component*

w : *Principal component explained variance*

2.6. Sensitivity test

Four weighting scenarios were used to test the sensitivity of results. One scenario involved equal weights and the three others were based on each class receiving higher weights than the two others (Table 3). These weights differ from those determined to measure the importance of the variables. The term 'variable weight' represents the weights utilized to determine the relevance of the selected variables in generating maps for each category, while 'sensitivity weight' was employed to highlight the importance of these categories as the three main dimensions of vulnerability.

This sensitivity test was conducted to determine the robustness of combining the maps from the three classes to obtain an overall vulnerability map. Proposing a balanced scenario where the vulnerability of the three classes was aggregated equally, and three scenarios in which one class had greater importance compared to the other two, allowed us to determine how sensitive the results were to fluctuations in the importance of each class. This approach is similar to that previously used by Jato-Espino et al. [39] to determine flood risk.

After checking the consistency of the results obtained in the sensitivity test, the vulnerability map was combined with the flood hazard index obtained for the same city by Manchado et al. [33]. The multiplication of the indices from both studies yielded a flood risk index for the city [70,71]. Because the vulnerability map and the hazard map did not fully align, the risk map covered only areas where both matched spatially, resulting in a slightly different area than the vulnerability map.

3. Results and discussion

3.1. Classification, screening and correlation

Of the 159 variables available per census tract, 57 were classified by the authors, and aligned with literature reviewed, as demographic, 84 as socio-economic and 18 as infrastructure (Table 4). The demographic class was reduced from 57 to 10 variables. Some of the variables are combined during our qualitative selection. Significant correlations were observed among some variables (total population with number of people under 16 and total population with sum of people under 16 and over 64,Fig. 3). As the variable of people over 64 was not correlated with any other variable, this and the variable of people under 16 were selected, whereas the two other variables were discarded.

In the socio-economic class, we selected 9 out of the 84 initial variables in Table 2. The income-related variables are highly correlated with one another, except for the percentage of the population below the poverty threshold (household income below 60% of the median income) (Fig. 3). We selected the variables with the highest cumulative correlation among the other income variables. We furthermore discarded the number of dwellings below ninety square metres and the marital status of unmarried. This decision resulted from the absence of correlation between the economic status of poverty with living in a smaller house and high correlation between the number of people with a mortgage or rent, respectively. For all modalities except poverty line, a negative correlation was ob-

Table 3
Proposed scenarios for sensitivity testing in the combination of the different vulnerability classes.

Scenario/Class	Sensitivity weights		
	Demography	Socio-Economics	Infrastructure
1	1/3	1/3	1/3
2	2/3	1/6	1/6
3	1/6	2/3	1/6
4	1/6	1/6	2/3

Table 4
Overview of the number of variables remaining after each selection step.

	Demography	Socio-economics	Infrastructure	Total
Initial	57	84	18	159
Screening	10	9	11	30
Correlation	8	4	6	18
PCA	7	4	5	16

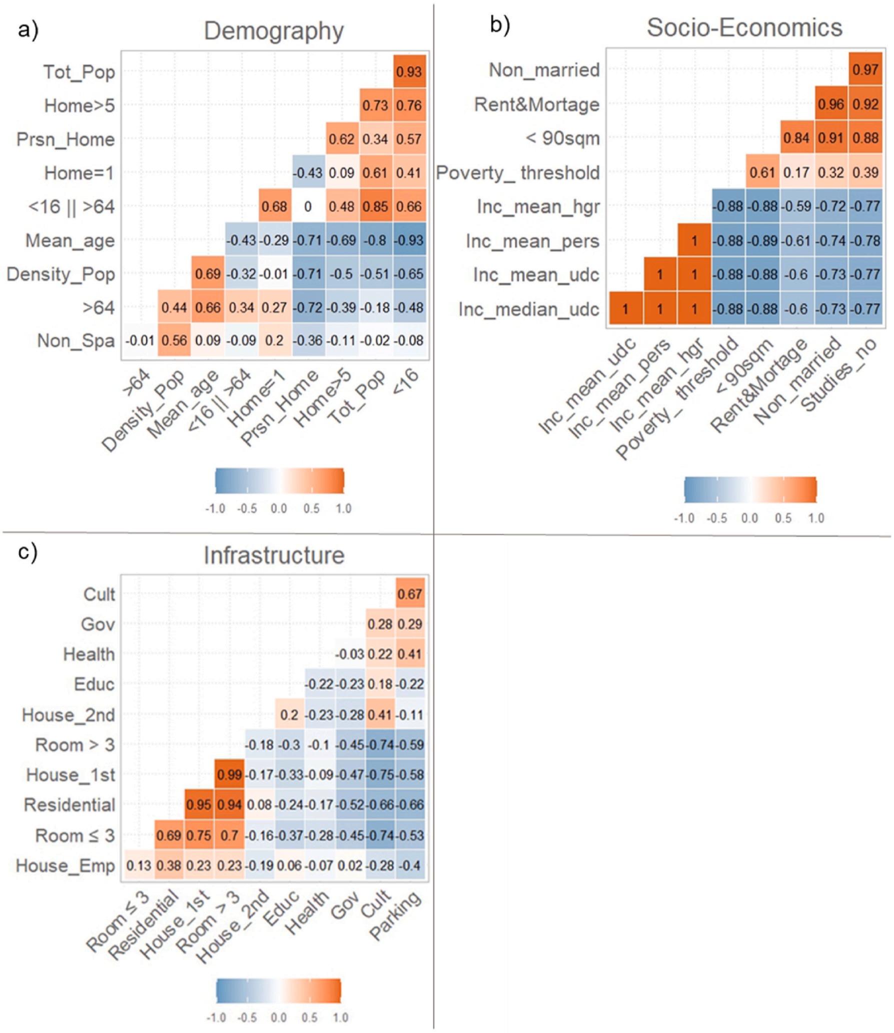

Fig. 3. Correlation between variables from the three classes of vulnerability. The 1's diagonal, characteristic of this type of plots, was omitted for better data visualisation. a) Demographic variables. b) Socio-economic variables. c) Infrastructure variables.

served with values very close to the threshold between civil status (not married) and income. A lower, albeit positive, correlation value was observed between a house size of less than 90 m^2 and people living below the poverty threshold.

In the infrastructure class, 11 of the 18 available variables were selected. However, disaggregated uses of residential buildings and differences in the number of rooms were discarded. This was because the main objective is to protect the main residences, and these are correlated with the aggregate data for all residential buildings.

3.2. Spatial vulnerability calculation

In the demographic class, the first two principal components account for 56.2% of spatial variability. When projected in the two-dimensional plane using the principal components, the selected variables are grouped in pairs (Fig. 4). Our results indicate positive spatial pattern relationships between the following pairs of variables: people over 64 years old and population density; foreign people and single-family families; families with more than 5 members and people under 16 years old. We also found a negative relationship between mean age and average home size.

Possible reasons behind these relationships in the demographic class can indicate that older people live in the most centrally located and densely populated areas in the city [72]. Moreover, according to the biplot, foreigners is related to single-person households may be an immigration-related behaviour, but also a form of behaviour of natives who do not leave their family unit individually [73]. However, in the previous correlation analysis this behaviour was not apparent. This discrepancy may be due to the fact that the principal components account for 50% of the spatial distribution. The other two relationships found in this class are related, as they indicate that the higher the number of people under 16 years of age, the higher the number of large families (more than 5). This is related to the fact that the lower mean age in the census tract, the higher average home size is. A possible explanation is that large

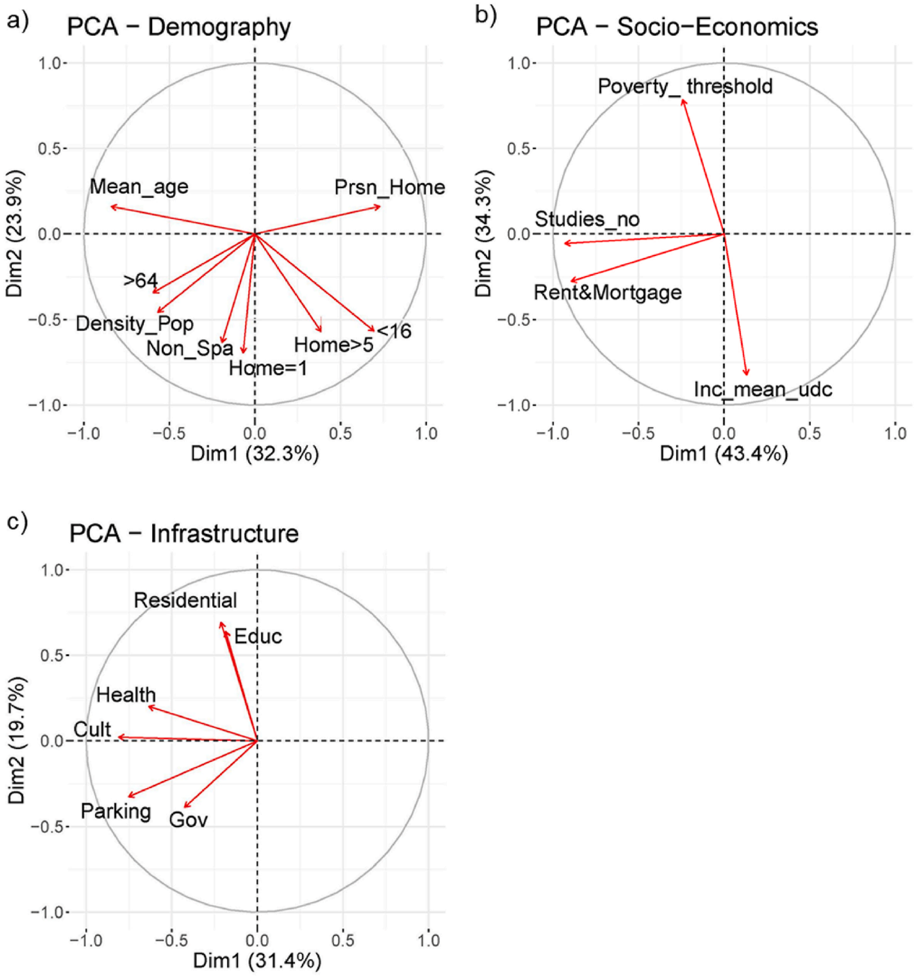

Fig. 4. PCA biplot showing the variances of main dimensions from principal component analysis. a) Demographic variables. b) Socio-economic variables. c) Infrastructure variables.

families consist of a larger number of children and census tracts where this type of family is prevalent tend to have a lower median age.

In the socio-economic class, the first two principal components explain 77.7% of the variability. Pairwise relationships occur between people who have no education and those who have a mortgage to pay or a rental housing contract, and between the average household income and the poverty threshold variable. In this class, the clearer relationships are found in the economic domain where the higher the income variable, the lower the poverty line. As for the class of infrastructure, only a spatial relationship between the number of residential buildings and the infrastructure for education is found.

3.3. Weighted sum and mapping subindices

Screening, correlation analysis and PCA progressively reduced the number of variables remaining in our selection (Table 4) after each step. For example, in the demographic class, the process is as follows: from the 57 variables originally available, 10 were selected through the screening process. Of these, 2 were discarded during the correlation analysis, leaving 8 variables. Subsequently, one variable was eliminated during the PCA analysis because it did not meet the required threshold of spatial explanatory percentage.

The weights of the variables that remained after the selection process were determined using Equation (1) (Table 5) (see Fig. 4). The higher the value of the weight, the greater variability in the data. The variables with no assigned weight (Density_Pop and Gov) were discarded during the PCA analysis due to their reduced contribution to either of the two principal components (Fig. 5).

When multiplying these weights by the values of the normalised variables disaggregated in each census tract (Fig. 6), the demographic class is found to contain 14 census tracts with high values. In the city centre, there are 12 census tracts with an over-aged or near-aged population and one census tract with high values of foreign population. Likewise, the 2 highest values are located in the periphery (south-west and north-east) and are characterised by a population with a large number of people under 16 years and/or with many single-person families.

Table 5
Weights obtained through the orthogonal sum of the contribution from final selected variables in each class. The variables that did not reach the minimum level of contribution in the two principal components analysed were scored as "-" and their value was 0.

Class	Variable Code	Orthogonal Sum Normalised Weight
Demography	<16	0.17
	>64	0.10
	Non_Spa	0.12
	Prsn_Home	0.16
	Home = 1	0.14
	Home>5	0.10
	Density_Pop	–
	Mean_Age	0.21
Socio economics	Poverty_ threshold	0.21
	Studies_No	0.29
	Inc_mean_udc	0.23
	Rent&Mortgage	0.27
Infrastructure	Residential	0.19
	Cult	0.26
	Health	0.16
	Gov	–
	Educ	0.16
	Parking	0.23

In the socio-economic class map, there are 2 sections with high values that match sections 1 and 3 of the demographic class ranking. In this case, this high value is caused by the presence of uneducated people, where 100% are children under the age of 16, and a number of households that are currently paying rent or a mortgage. The latter indicates, in contrast to the city centre, that these individuals have just settled in this area and are more financially vulnerable than those from areas where housing is not currently a financial effort.

As for the infrastructure class, the subindex is strongly dominated by the large number of universities in one of the census tracts. The next 4 census tracts with the highest infrastructure vulnerability value are also characterised by a high number of educational centres. This highlights the great spatial variability of educational centres between the different census tracts in the city. This variable has implications of direct vulnerability for workers and students, but also for relatives of these students, who might be indirectly affected if these infrastructures are impacted by floods.

3.4. Sensitivity test

Sensitivity test results show that there is an area in the southern periphery where high vulnerability is observed in all scenarios, although this effect is less pronounced with higher weights for the infrastructure class (Fig. 7). In the equal weight's scenario, we find vulnerable areas in the city centre bordering the bay area (south from centre). In general, no anomalies were found within the weighted sums and the values are not sensitive to weight variations. Therefore, in the following section the equal weights were considered for further study.

3.5. Risk map

Vulnerability and hazard maps often do not highlight the same hotspots. This is due to the fact that hazard is usually high along rivers, flow accumulation areas or near the coast, whereas the distribution of vulnerability is determined by variables such as those suggested in Table 2. This vulnerability map calculated with the balanced scenario shows four high-scoring zones. These zones have no particular pattern in terms of the physical orography of the city. They are characterised by large numbers of children under the age of 16, a higher number of people paying rent or mortgage and a concentration of educational facilities. Also, in this case of study, the hazard map covers a slightly smaller area than the vulnerability map. This is due to spatial resolution limitations in the calculation of sub-catchment areas in coastal zones during the analysis of the accumulated runoff [33]. However, we represent all census tracts in Fig. 8.

The resulting risk map shows 3 high risk areas, one in each of the main catchments of the city. The area to the northwest consists of detached houses with minimal other development. The corresponding census tract is a large area with the majority population residing in the southern part outside the hazard zone, avoiding high risk. Another high-risk zone is near the eastern wetland, where several of the city's main roads are at risk. Finally, a high-risk zone near the city centre is characterised by dense urbanisation, funnelling in the runoff from high and impermeable areas to this zone.

3.6. Discussion

This study proposed a solution for variable reduction. In previous studies, selection of variables was made exclusively based on data availability, subjective criteria [54] or correlation analysis [74]. We followed a hybrid procedure using statistical techniques to select those available datasets that explain most of the vulnerability. In terms of covering most of the vulnerable elements within the city this study improves on previous studies where only the social scope is assessed such us Social Vulnerability Index (SoVI) [75] currently used worldwide [54,76].

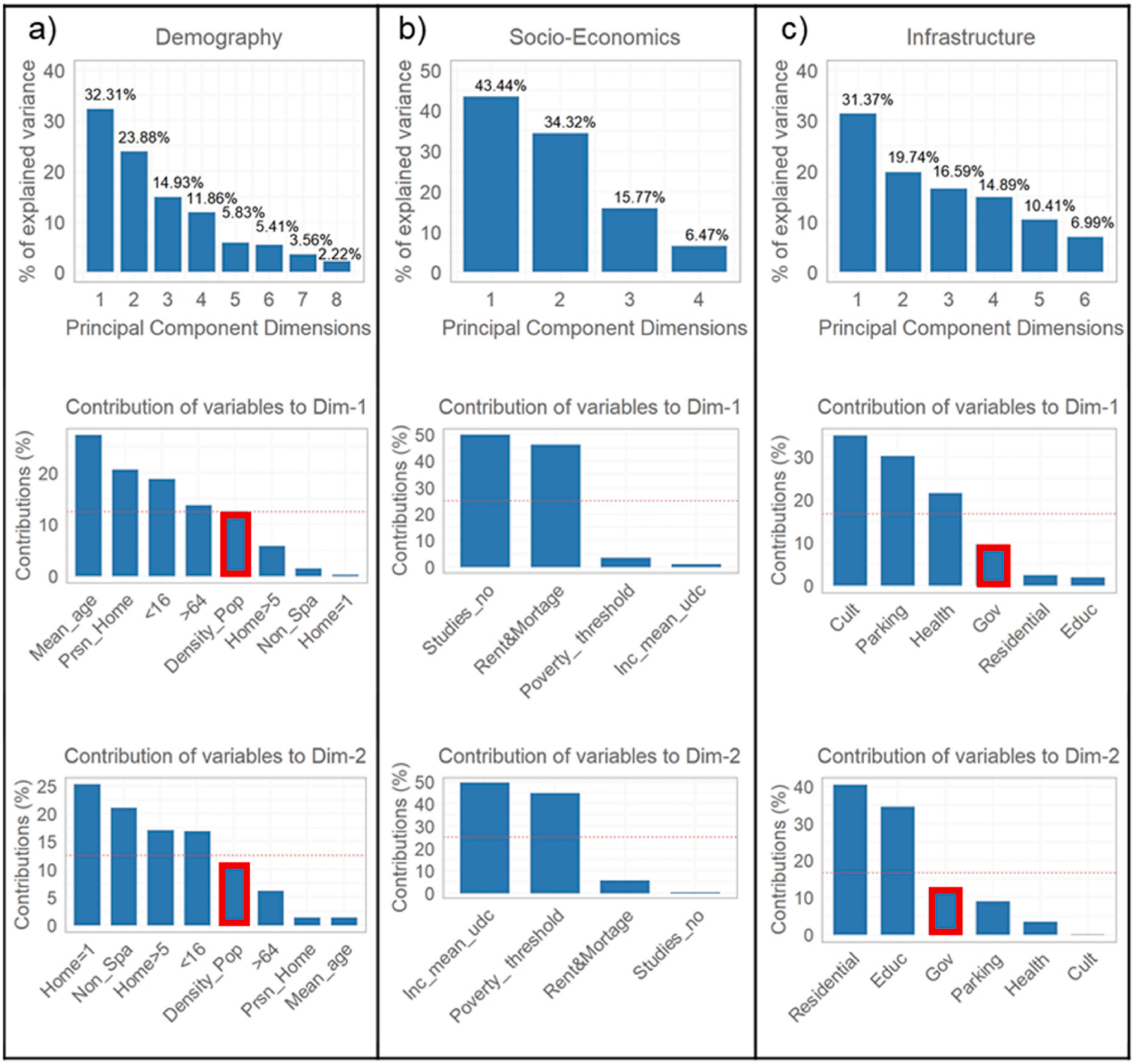

Fig. 5. Percentage of variance explained by each dimension of the principal components (top row) and contributions of each variable o dimensions 1 and 2 (second and third row). The dotted line represents the threshold defining the significance of that contribution. The bars outlined in red refer to the variables that were discarded during the PCA analysis because they did not contribute to either of the two principal components. a) Demography b) Socio-economics c) Infrastructure. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

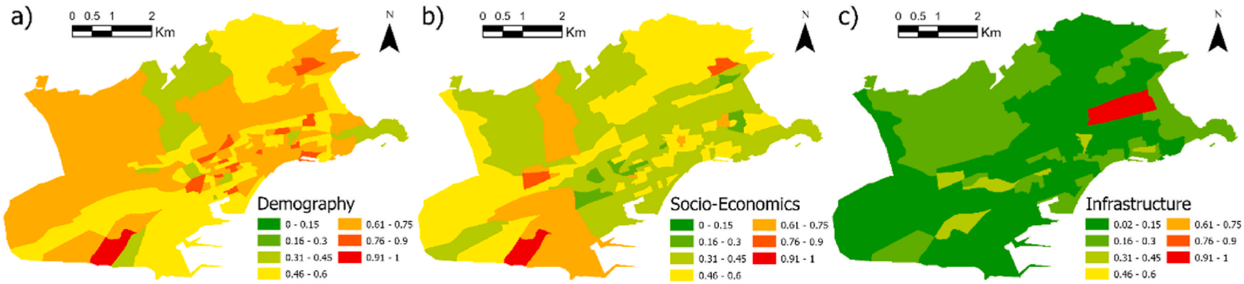

Fig. 6. Vulnerability subindex created per class. a) Demographic. b) Socio-economy. c) Infrastructure.

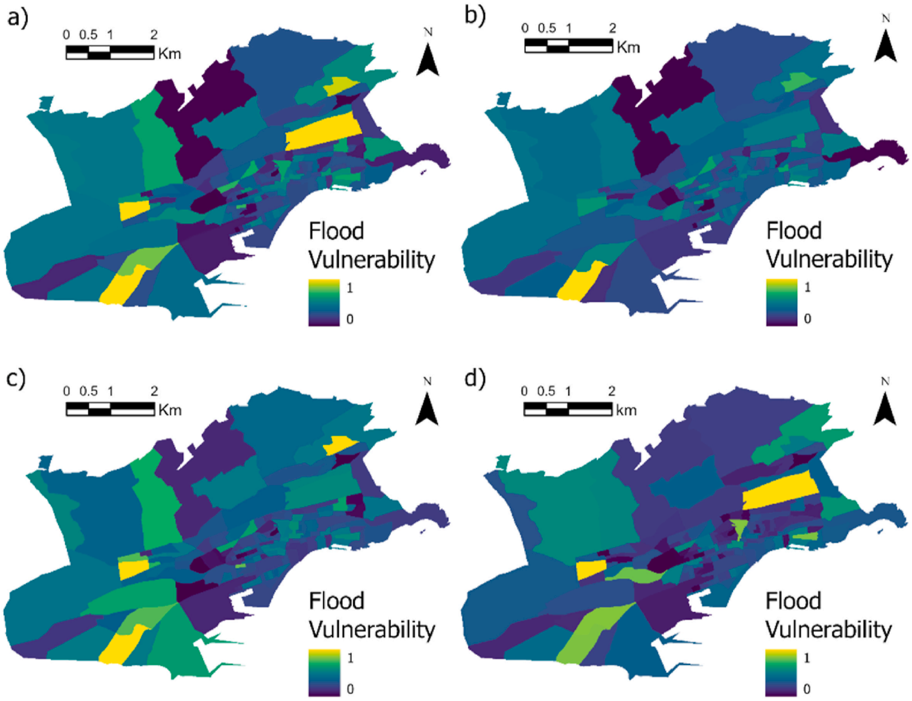

Fig. 7. Sensitivity to class weights. a) Equal weighting, b) 2/3 demographics c) 2/3 Socio-economy d) 2/3 Infrastructures.

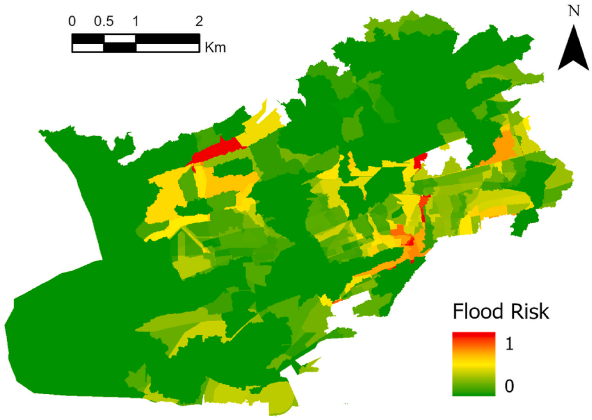

Fig. 8. Flood risk map of Santander, created by combining the vulnerability map from our study and the hazard map of Manchado et al. (2021).

Infrastructure failures are one of the main causes of extensive flood damage, highlighting their importance in risk assessment [77]. We include the vulnerability of critical infrastructure, which is not a category considered in most of the literature on urban flood vulnerability indices recently. This provides a holistic view of the vulnerability to flooding.

Targeting vulnerable populations in the city improves preparedness and relief efforts [20,78]. The methodology followed has enabled selecting the most relevant variables and identifying areas with the greatest vulnerability.

Our results align with previous studies, particularly for the city centre of Santander [39] and are also similar to the Municipal Emergency Plan that the Santander City Council published in 2016 to identify flood risk hotspots [79].

This analysis demonstrates that the most vulnerable areas of Santander were determined by variables such as children under 16 years of age, the highest number of people paying rent or mortgage and the highest concentration of educational facilities. These results are consistent with previous studies on vulnerability in other parts of the world, where it has been shown that these variables are also significant. Children are a group with limited capacity to deal with floods, and their dependence on survival during floods has been observed in the Greater Manchester (UK), Aotearoa (NZ) or USA [80–82]. Similarly, individuals with mortgage-related debts are the primary cause of vulnerability to flooding in low-income communities in the state of Louisiana (USA) [83]. Additionally, individuals with low educational attainment are correlated with flood risk areas in Virginia [84]. In relation to education, it has been reported that critical infrastructure most affected by floods is often related to educational facilities [85,86]. These variables could even have a more pronounced effect in areas of emerging economies with more difficulties to support these population groups [87–90].

There was no significant contribution to variability from population density (demographic class) and government buildings (infrastructure class) (Fig. 5). This does not imply that these variables are not relevant for vulnerability, but they are homogeneous across census tracts. Even variables discarded in the correlation analysis may be relevant for other locations.

It is therefore advisable to perform the full methodology when analysing other case studies to find the relevant variables. There are certain problems in poorly populated areas where these census tracts are too large for an accurate assessment of vulnerability. Therefore, special attention needs to be paid to those areas on the periphery of the city, where the population density is lower when combining vulnerability and hazard data.

4. Conclusions

In this study, variables related to flood vulnerability were selected and classified from a national database to study their spatial distribution within the city of Santander throughout its census tracts. This was done by means of a methodology based on relevant variables and analysing them statistically. Then, the variables were weighted to produce a vulnerability index based on 3 different vulnerability classes, demographic, socio-economic and infrastructures. Finally, a risk map was obtained by combining the results of vulnerability with those of hazard derived from a previous study in the same area.

The method was satisfactory in determining the most significant variables and areas within a city. Specifically, this study has identified two areas in the city of Santander with a high demographic and socio-economic vulnerability and one area with a high vulnerability due to the infrastructures it contains. In addition, 3 critical areas were found in terms of flood risk, one for each main catchment areas of the city. The disaggregation of the data in the different census tracts used to obtain the vulnerability index may be used for any city in Spain. These data and their corresponding temporal updates enable observing the evolution of the same city over time.

There are some ways in which the proposed methodology flood risk management can be improved. First, by obtaining a spatially improved database in order to have a stronger foundation to assess vulnerability. Second, by automating the methodology to enable analysing the temporal evolution of the same city and also the spatial comparisons between different cities. Finally, it would be interesting to spread the use of this methodology to study vulnerability in cities to other environmental problems.

Thanks to this study of critical areas, mitigation measures can be taken to reduce flood vulnerability. Thus, urban planners could make use of GIS applications and establish new scenarios that reduce the social impact of these natural events as efficiently as possible, helping administrations to make optimal use of their resources against climate change and its possible adverse effects.

Credit author statement

Alejandro Roldán-Valcarce: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – Original Draft, Review & Editing, Visualisation. **Daniel Jato-Espino:** Conceptualization, Methodology, Formal analysis, Writing – Review & Editing. **Cristina Manchado:** Formal analysis, Writing – Review & Editing. **Peter M. Bach:** Methodology, Formal analysis, Writing – Review & Editing. **Martijn Kuller:** Methodology, Formal analysis, Writing – Review & Editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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