

Socioeconomic vulnerability to wildfires: A case study in Galicia, NW Spain

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Introduction

Wildfires constitute a recurring natural risk, with greater consequences on the population of areas with human settlements in contact with the vegetation, the Wildland Urban-Interface (WUI). The number of people living in these areas has increased dramatically in recent years (e.g., Radeloff et al. 2018), raising wildfire risk and a growing concern, both for the environmental damages caused by fires, as well as for endangering properties and human lives. Scientific research indicates that the actions taken by the population for their protection reduces firefighting expenditures. It is essential, therefore, to have greater knowledge of the affected population and the factors that influence the potential impacts on it (Calkin et al. 2014). These aspects have been examined by many authors, in relation to forest fires under the term "vulnerability" (Paton and Tedim 2012). Previous studies on social vulnerability to forest fires indicate that the socially more vulnerable population has a lower capacity to apply mitigation measures against forest fires and recovery in the event of occurrence (Gaither et al. 2011; Paveglio et al. 2016; Wigtil et al. 2016). In this sense, knowledge is still lacking regarding how social vulnerability is affected by wildland fuels management decisions and building materials used in wildfire hazard areas. In addition, after a disaster, the resilience of societies depends not only on the income of individuals, but also on age and health status, which leads to the concept of environmental justice. The overall objective of this work is to spatially identify the vulnerability of the population to forest fires. As a case study, we select the autonomous region of Galicia because it registers the highest occurrence of fires in Spain (40% of the total) and where the consequences can be very important for the population. We use socioeconomic and demographic variables at the municipal level to construct a spatial social vulnerability index (Cutter et al. 2003), which can pinpoint the most vulnerable areas to wildfire impacts. The resulting map can be used to identify specific locations where it improvements in preparedness and suppression capacity may yield the largest gains in social resilience to natural risks.

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Materials and methods

Our social vulnerability index development began with a literature review and an assessment of data availability at the municipality level. Most data used in the analysis are from 2017 and 2018, but when necessary we have used data for other years or aggregated data for a longer period of time. The majority of the data were provided by the Galician Statistics Institute (IGE). The base spatial unit in our study is the municipality, 313 in total in Galicia. We began with a list of 83 potentially useful variables, which was subsequently shortened due to multicollinearity problems and high uniqueness. Finally, the analysis was reduced to 21, assigning the mean value to the few cases with missing data. The list of variables selected in this work is presented in Table 1. These variables were primarily selected based on their availability and their ability to measure multiple dimensions of social vulnerability: demographic and economic structure, education, and social dependence. High income provides a means to minimize damages in case of a wildfire. We measure personal income by including variables such as gross disposable income per capita. Education is also linked to socioeconomic status, employment opportunities, and health. We measure the level of education by including the percentage of population with fewer than 5 years of education. At the same time, the number of teachers working in the municipality was considered. People who are dependent on social services will require additional support in case of wildfire. We then include variables considering all people beneficiaries of the Income of Social Integration (RISGA) and the Social Inclusion Assistance (AIS), as well as the total number of people receiving a Non-Contributory State Pension, and the number with any kind of disability. Also the number of people working in primary health care. The presence of disadvantage people in the municipalities were measured also by including variables for the percentage of unemployed. Workers in the primary sector are more likely to be affected if a wildfire occurred. Thus, the percentage in the municipality was considered, as well as the percentage of workers in the tertiary sector. To account for vulnerability due to age structure, we considered several variables: the average age in the municipality, the percentage of people under 5 years and older than 64 years old. Due to gender inequalities, long term unemployed women were also considered, as well as the percentage of women with more than 85 years old. We consider several variables to account for the growth of the population, such as the compound annual growth rate and the natural growth rate in the last ten years, as well as the population density. Finally, the number of people per household and the number of household without a car were included in order to capture some characteristics of the households.

We examined the distribution of vulnerability to wildfires in Galicia at the municipal level following methods developed by Cutter et al. (2003), combined with available data in order to characterize socioeconomic vulnerability. The development of a social vulnerability index is based on Principal Components Analysis (PCA), which is a statistical technique that deals with a large set of variables and extracts a few number of factors to enhance their interpretability. We performed PCA in order to explain the largest share of total variance in the set of the selected variables. We applied Kaiser's criterion, only keeping the factors with eigenvalues greater than 1, and we applied the varimax rotation method. We assigned each variable to a certain factor based on its maximum absolute factor loading, meaning that if the highest absolute loading is negative, higher values of a specific variable relate negatively to the assigned factor. A factor

label has to be assigned to describe the set of variables associated with each factor. The factor scores were calculated with regression scoring methods. The resulting social vulnerability scores are standardized. The vulnerability index for each municipality was obtained by summing all the factors using equal weighting, following Cutter et al. (2003). We classified municipalities with z-scores less than -1.5 as having very low social vulnerability, between -1.5 and -1.0 as low, between 1.0 and 1.5 as high, those with z-scores greater than 1.5 as very high and remaining municipalities (between -1.0 and 1.0) as moderate vulnerability. The resulting social vulnerability index allows for a ranking of different spatial units in order to identify priority locations for hazard management. In this way we determined the relative index that represents how vulnerability varies across space. We then mapped this information to show whether there is coincidence of social vulnerability and wildfire risk in terms of number of wildfires and burned area per ha.

Table 1. List of variables to create the social vulnerability index.

Name	Definitions	Year
rdbcap	Gross Disposable Income per capita (euros)	2016
loweducation	% illiterate and with less of 5 years of studies	2001
teachers	Number of teachers working in the municipality	2018
risgaman	% men beneficiaries of the Income of Social Integration (RISGA) and the Social Inclusion Assistance (AIS) (%)	2017
risgawoman	% women beneficiaries of the Income of Social Integration (RISGA) and the Social Inclusion Assistance (AIS) (%)	2017
nocontribtot	% people receiving State pension (non-contributory) (%)	2017
dissability	% people with any kind of dissability	2017
health	Number of people working in primary health care	2017
unemployed	% unemployed people between 14 e 65 years	2018
primary	% workers in the primary sector	2018
tertiary	% workers in the tertiary sector	2018
meanage	Mean age	2017
pob5	% population under 5 years old	2018
pop64	% population older than 64 years old	2018
wom1year	% long term unemployed women	2018
wom85	% women older than 85 years	2018
tcaapop	Compound annual population growth rate in the last ten years (%)	2009-2018
natural	Natural population growth rate in the last ten years (%)	2009-2018
popdensity	Population density (N° of people/km ²)	2018
pophousehold	Average number of people per household	2001
nocar	% households without car	2001

Results

After performing PCA, five components with eigenvalues greater than 1.0 were extracted, which jointly captured 80% of the variance. Table 2 shows the factor labels with the sign, percentage of

the variance explained, and the number of drivers included in each factor and their loadings. The five factors are labeled Population structure and evolution, Education and health, Unemployment and handicapped population, Economic activity, and Poverty. Each factor has a sign indicating its positive or negative effect on social vulnerability, based on the main drivers in each factor. The first factor, Population structure and evolution, is dominated by variables that imply lower mean age, lower population over 64 years old, higher natural population growth rate, lower number of households without car, higher compound annual population growth rate, higher number of people per household, lower percentage of illiterate individuals and those with less than 5 years of schooling, and higher Gross Disposable Income per capita. Together, these variables contribute to a lower vulnerability and this factor has a negative sign. The second factor, Education and health, identifies mainly those municipalities with higher numbers of people working in primary health care and in education, as well a higher population density. Thus, this factor reduces vulnerability, and so a negative sign is assigned. The third factor, Unemployment and handicapped population, is mainly showing those municipalities with a high percentage of people with disabilities, long term unemployed women, unemployed, people receiving non-contributive state pensions, and a high percentage of women over 85 years old. All of these increase social vulnerability, thus a positive sign is assigned. The fourth factor, Economic activity, represents municipalities with lower percentages of people working in the primary sector and higher percentages in the tertiary sector, which each may be associated with lower social vulnerability to wildfires. Therefore, a negative sign is assigned to this factor. Finally, the fifth factor, Poverty, represents those municipalities with higher percentages of beneficiaries of the Income of Social Integration (RISGA) and the Social Inclusion Assistance, both in men and women, which contributes positively to social vulnerability. Thus, a positive sign is assign to this factor.

Table 2: Factors labels, factor loadings, % of the variance explained and factor sign adjustment for the social vulnerability index.

Factor label	% of the variance explained	Sign	Nº of drivers	Drivers (Loadings)
Population structure and evolution	37.37	-	9	meanage (-0.944), pop64 (-0.943), natural (0.909), nocar (-0.885), pop5 (0.878), tcaapop (0.816), pophousehold (0.764), loweducation (-0.618), rdbcap (0.567)
Education and health	16.48	-	3	health (0.943), teachers (0.931), popdensity (0.859)
Unemployment and handicapped population	10.15	+	5	dissability (0.737), woman1year (0.716), unemployed (0.677), nocontribtot (0.615), woman85 (0.476)
Economic activity	8.75	-	2	agriculture (-0.836), tertiary (0.833)
Poverty	6.40	+	2	risgaman (0.916), risgawoman (0.897)

Figure 1 shows the spatial distribution of social vulnerability, with the highest vulnerability associated with municipalities of the interior of the region, mainly located in the provinces of Pontevedra and Ourense. Comparing this map with the distribution of past wildfire occurrences, number of wildfires per ha (Figure 2a), and burned area in relation to total municipality area (Figure 2b), several municipalities present a high social vulnerability and a

past high risk of wildfires. Most of these are located in the interior and southern areas of A
Coruña and Pontevedra provinces.

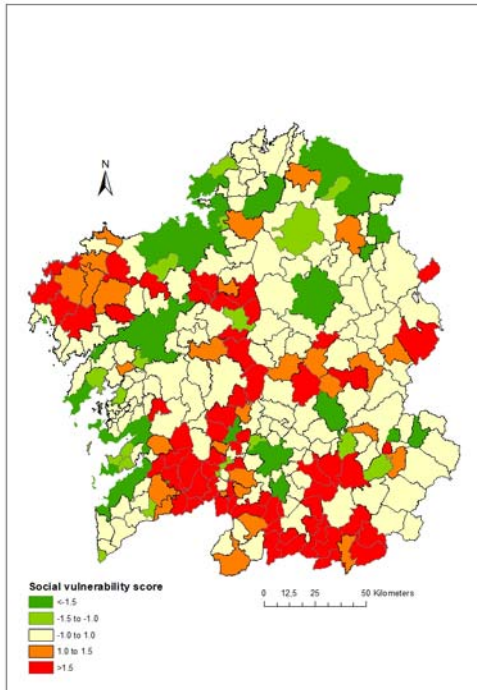


Figure 1: Social vulnerability index.

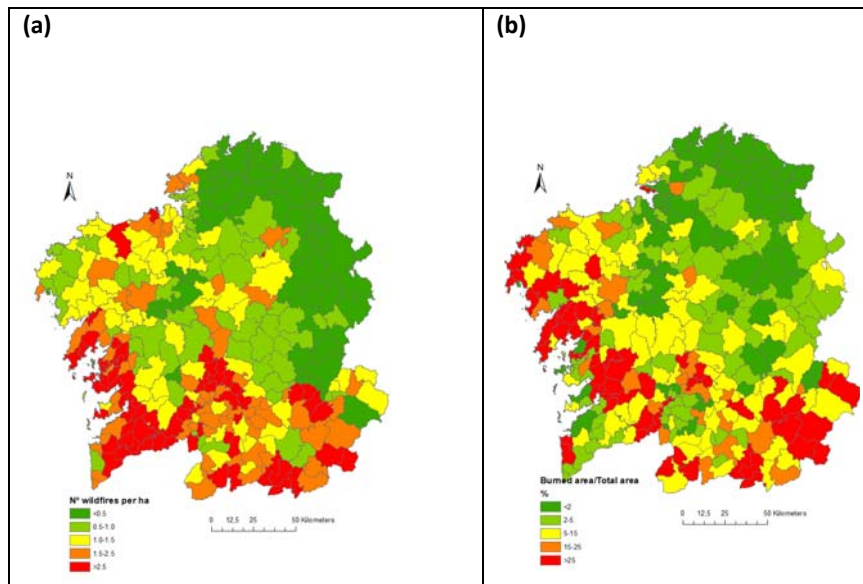


Figure 2: Wildfires by municipalities in the period 2006-2016: (a) Number of wildfires per ha and (b) Burned area in relation to total municipality area (%).

Conclusions

This work has analyzed social vulnerability to wildfires in Galicia (NW Spain). We detected clusters of municipalities with high vulnerability and high risk of wildfires. This information is of potential importance to policy makers, since it identifies those locations in the region where efforts to improve preparedness may be focused, resulting in increased social resilience to wildfires. Further analyses could be developed in the future, including an identification of location hotspots for both social vulnerability to natural hazards and wildfire risk.

Acknowledgments

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References

- Calkin DE, Cohen JD, Finney MA, Thompson MP (2014). How risk management can prevent future wildfire disasters in the wildland-urban interface. *Landscape and Urban Planning* **119**, 44–53.
- Cutter S, Boruff BJ, Shirley WL (2003). Social vulnerability to environmental hazards. *Social Science Quarterly* **84**, 242-261.
- Gaither JC, Poudyal NC, Goodrick S, Bowker JM, Malone S, Gan J (2011) Wildland fire risk and social vulnerability in the Southeastern United States: An exploratory spatial data analysis approach. *Forest Policy and Economics* **13**, 24–36.
- Paton D, Tedim F (2012) *Wildfire and community: Facilitating Preparedness and Resilience*. Charles C Thomas Publisher.
- Paveglio T, Prato T, Edgeley C, Nalle D (2016). Evaluating the Characteristics of Social Vulnerability to Wildfire: Demographics, Perceptions, and Parcel Characteristics. *Environmental Management* **58**, 534-548.
- Radeloff VC, Helmers D., Kramer HA, Mockrin MH, Alexandre PM, Bar-Massada A, Butsic V, Hawbaker TJ, Martinuzzi S, Syphard AD, Stewart SI (2018) Rapid growth of the US wildland-urban interface raises wildfire risk. *PNAS* **115**, 3314-3319.
- Wigtil G, Hammer RB, Kline JD, Mockrin MH, Stewart S, Roper D, Radeloff VC (2016) Places where wildfire potential and social vulnerability coincide in the coterminous United States. *International Journal of Wildland Fire* **25**, 896–908.