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Spatial patterns of social vulnerability in relation to wildfire risk and wildland-urban interface presence

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Abstract

Wildfires have greater impacts on socially vulnerable communities. Identifying these vulnerable communities and enhancing understanding of what influences their susceptibility to wildfires can guide the design of spatially targeted strategies in preparedness, mitigation plans, and adaptation strategies. This paper investigates the heterogeneous spatial coincidence of social vulnerability and wildfire risk in Galicia (Spain) at the municipality level. Results show that socioeconomic status, rates of dependence on social programs, and household unit characteristics are factors that contribute the most to social vulnerability. In general, municipalities with the highest proportion of their area in the Wildland-Urban Interface (WUI) have the lowest social vulnerability. Within Galicia, locations with high social vulnerability and high wildfire risk are spatially concentrated in the south and tend to be low-population density communities, often in remote locations and with relatively high percentages of elderly people. Our findings provide an empirical foundation for wildfire management planning that accounts for the spatial distribution of vulnerable communities.

Keywords

Social vulnerability, Wildfires, Wildland-urban interface, Natural hazards, Galicia, Spain

Highlights

- Our analysis facilitates spatial prioritization of investments in wildfire protection planning
- Wildfire risk preparedness strategies that consider the socially vulnerable could benefit society
- Wildfire risk is higher in socially vulnerable municipalities
- Socially vulnerable residents often live in municipalities with a lower share of wildland-urban interface land

Introduction

Indicators of social vulnerability to natural hazards have received increasing attention by analysts in recent years (e.g., Cutter et al. 2003; Wisner et al. 2004; Birkmann et al. 2013; Frigerio et al. 2018). Identifying where the most vulnerable populations are located and what are the socioeconomic characteristics that determine vulnerability are critical elements for reducing wildfire risks and for developing and enhancing policies to mitigate human impacts (e.g., Birkmann 2006; Cutter et al. 2009; Cardona et al. 2012). Measuring social vulnerability is challenging because of the complex set of factors affecting damages. The spatial variation in hazards is not only connected to biophysical factors—they are also associated with communities' abilities to plan for, comply with, resist, and respond to damaging events (Spielman et al. 2020). Vulnerability is socially constructed within a specific historical, institutional, and socioeconomic context (Cutter et al. 2003; Cutter and Finch 2008). Factors such as age, gender, income, wealth, health, the level of education, and the strength of institutions and social organizations that enhance coping capacity, have been shown to determine the vulnerability of individuals to a range of hazards: floods and cyclones (e.g., Hamidi et al. 2020), earthquakes (e.g., Schmidtlein et al. 2011), droughts (e.g., Otto et al. 2017), and volcanic eruptions (e.g., Siagian et al. 2014). Social vulnerability depends on more than simply the probability of occurrence of a particular natural hazard. For example, land use regulations can affect the damages derived from rapid-onset hazards such as cyclones, flash floods, earthquakes, and wildfires, because the temporal window for warning and response by affected populations is limited (Tapsell et al. 2010). This paper focuses on wildfires as a recurring threat whose outcomes, in terms of frequency, severity, spatial pattern, and social and environmental impacts, are significantly related to societal factors (e.g., Paton et al. 2015).

Recent years have seen many extreme wildfires worldwide (Tedim et al. 2018), such as the 2017 wildfire season in the Iberian Peninsula, Greece (2017-2018), California (2020), Chile (2017), and Australia (2019-2020), with an expectation that the frequency of such extreme wildfire events will increase with climate change (Shukla et al. 2019). The responsibility for managing wildfire risk usually falls on government agencies, which tend to rely on risk quantification to prioritize locations based mainly on biophysical variables (e.g., topography, soils, vegetation, climate, and hazardous fuels (Palaiologou et al. 2019). Several studies have advanced tools and methods that pay attention to biophysical factors connected to vulnerability, including Duguy et al. (2012), Aretano et al. (2015), and Lecina-Díaz et al.

(2021). Some research has also assessed the expected impacts of wildfires, connecting them to ecological conditions, ecosystem services provision, and socioeconomic factors such as the value of affected houses, or linking wildfire impacts to human population levels and forest management (e.g., Chuvieco et al. 2014; Oliveira et al. 2018). However, such analyses are limited in their accounting for some of the social drivers that may explain how social vulnerability varies spatially across landscapes and communities. Addressing this shortcoming is an essential component to advancing approaches to spatial prioritization of investments in wildfire protection planning (Poudyal et al. 2012).

The limited existing research on spatial variability in wildfire social vulnerability has documented a high degree of variation in its relationship to wildfire risk (e.g., Poudyal et al. 2012, Wigtil et al. 2016, Paveglio et al. 2018; Davies et al. 2018). For example, Gaither et al. (2011) found that high social vulnerability/high wildland fire risk areas are prevalent in less densely populated rural areas, as these communities are less likely to be engaged with wildfire mitigation programs, such as those that focus on hazardous fuel reductions. Wigtil et al. (2016) showed that places with high wildfire potential have, on average, lower social vulnerability than other places but that nearly 10% of all housing in places with high wildfire potential also exhibit high social vulnerability. Davies et al. (2018) determined that wildfire vulnerability is spread unequally across ethnicity and race, finding moderate wildfire hazard and high social vulnerability in the southeastern U.S. In a study for North Carolina, Andersen and Sugg (2019) revealed that social vulnerability varies greatly across the region and that areas with smaller wildfires tend to be communities with lower social vulnerability. Palaiologou et al. (2019) found that areas with high vulnerability are disproportionately exposed to wildfire. Evidence in other countries includes the study of Akter and Grafton (2021), which revealed a significant positive relationship between an indicator for socio-economic disadvantage and wildfire exposure in Australia, quantified by an index of wildfire proximity to communities; and Nunes and Lourenço (2018), which offered evidence in Portugal of a strong spatial association between wildfire incidence and socioeconomic factors often linked to vulnerability, such as income and the elderly population.

This paper builds on this emerging research into the spatial variability in wildfire social vulnerability by evaluating the social factors linked to vulnerability and the concentration of socially vulnerable populations residing in areas of high wildfire risk, in a Mediterranean European context, Galicia (NW Spain). Our work complements recent findings connecting natural risk and social vulnerability by focusing on areas where urban development meets or intermingles with wildland, i.e., the wildland-urban interface (WUI). The emerging science of vulnerability connected to the WUI (e.g., Wigtil et al. 2016) is growing in importance managerially, economically, and in policy circles because of the increase in wildfire risk across many parts of the world (e.g., Radeloff et al. 2018, Buechi et al. 2021). The choice of our studied region, Galicia (NW Spain), is relevant because it registers the highest rate of occurrence of wildfires in Spain, comprising 30% of total area burned (MAPAMA 2019), and because of high levels of human exposure to wildfire: 13% of the territory is classified as WUI (Chas-Amil et al. 2020). If WUI areas are found to be socially vulnerable, then this raises the prospect of continued and rising rates of human suffering from wildfire in the future.

Our research addresses three main questions: (a) what is the spatial pattern of social vulnerability in Galicia?, (b) where is there a spatial coincidence of high social vulnerability and high wildfire risk?, and (c) are communities in areas with a high share of wildland-urban interface land also more socially vulnerable?

To answer these questions, we apply a hazard-of-place approach measuring social vulnerability to create a composite indicator, a Social Vulnerability Index (SoVI) (Cutter et al. 2003), as a quantitative measure derived from a series of observed facts that summarize the complexity of inequalities among different communities (OECD 2008). The index allows for the identification of the main drivers of relative vulnerability across a specific landscape and enables comparisons of the degree of vulnerability across locations (Coughlan et al. 2019). Based on historically observed wildfire events in Galicia (28,446 fires and 200,040 ha burned, spanning 2010-2018), we investigate and map the spatial coincidence of social vulnerability and wildfire risk. Wildfire risk is characterized by two alternative measures: the number of wildfires per unit area, and the wildfire area burned per unit area.

Materials and methods

We investigated the spatial distribution of social vulnerability to wildfires in Galicia based on a hazard-of-place approach to quantify differences between residents across municipalities, 313 in total, using the SoVI index. These index results were combined with historical data on wildfire events to analyze, categorize, and map the coincidence of social vulnerability and wildfire risk.

Principal Components Analysis (PCA), a multivariate statistical technique that extracts a few components from a large set of variables to enhance their interpretability, was used to develop the social vulnerability index. As in other vulnerability studies (e.g., Chen et al. 2013), the availability of public data was a determinant in the selection of variables for this study. An initial list of potential variables at the municipal level was subsequently shortened to address multicollinearity among potential variables. Fourteen variables were retained to create the social vulnerability index, using data, mostly from 2020, compiled from the Galician Statistics Institute (IGE). Table 1 provides short definitions and basic statistics relating to each variable.

Before the application of PCA, due to different measurement units, we normalized all variables using z-score standardization. Moreover, following Tate (2012), we reversed the directionality of the standardized variables that presented high values associated with low levels of social vulnerability. Thus, large positive values for all variables imply higher social vulnerability.

Kaiser's eigenvalue-greater-than-one rule, parallel analysis, and scree plot were used to confirm the number of components (Zwick and Velicer 1986). The interpretation of the components was facilitated by the application of varimax rotation to the component matrix. We assigned each variable to a particular component based on its maximum component loading. We used IBM SPSS Statistics 20 software for the PCA.

A component label was assigned to describe the set of variables associated with each component, from which scores were calculated with regression scoring methods. The social vulnerability score for each municipality was obtained by calculating a sum of the component scores that were weighted by the proportion of variance explained by each component. This weighting approach gives greater importance to the components that explain a larger proportion of the variance of the variables included in the PCA (Schmidtlein et al. 2008; Wigtil et al. 2016). We normalized the resulting social vulnerability scores by municipality using z-score standardization, which allows for a ranking of different spatial units, representing how vulnerability varies across space. Following Cutter et al. (2003), we mapped social vulnerability considering five classes: less than -1.0 as having a very low social vulnerability, between -1.0 and -0.5 as low, between 0.5 and 1.0 as high, greater than 1.0 as very high, and then assigning municipalities with indices between -0.5 and 0.5 as moderate vulnerability. To investigate whether vulnerability scores were spatially clustered, we calculated the univariate global Moran's I (Anselin 1995) using Geoda™ 1.18.0. The univariate global Moran's I ranges between -1 and 1, with a value of zero when there is perfect randomness.

We used two variables to characterize wildfire risk in each municipality: (i) the number of wildfires (counts) per hectare, and (ii) the percentage of land area burned in the period 2010-2018 (Table 1). Wildfire counts were obtained from the Spanish Forest Service, while the wildfire perimeters used to calculate the area were collected from the Galician Geographical Information System (Xunta de Galicia). WUI land classifications followed Chas-Amil et al. (2020) (area within a 50 m radius around buildings at a distance of up to 400 m from a forested area). We also used information at the municipality level on the number of buildings from the Galician Topographic Base 1:10,000 (BTG 2016), and the number of inhabitants from the Nomenclátor - Galician Statistical Institute.

A classification of the level in which the municipalities have been exposed to wildfire risk (number of wildfires per ha and burned area per ha) and the incidence of WUI (percentage of municipality area) was based on the quartiles of each variable: very low, low, moderate, high, and very high. We first evaluated the coincidences of each of the wildfire risk measures with social vulnerability through cross-tabulation. To assess the existence of significant differences in social vulnerability scores by the two categories of wildfire risk and WUI incidence, we used the Kruskal-Wallis test. Spatial correlations between wildfire risk and social vulnerability as well as between wildfire risk and WUI incidence were also computed, using the bivariate global Moran's I statistic and their spatial coincidence was quantified with the bivariate local Moran's I (I_i) (Anselin 1995):

$$I_{i=z_{x_i}} \sum_j w_{ij} z_{y_j}$$

where x is vulnerability score at location i, and y is wildfire risk or WUI incidence measured in its neighbors j, z indicates that the variables are standardized, w_{ij} is the spatial weight. In the calculation of this statistic, a first-order queen contiguity was selected. Pseudo p-values were generated using 999 permutations. Hotspots (high-high clusters) and coldspots (low-low clusters) were detected where the spatial association between social vulnerability scores and wildfire risk or WUI incidence was positive. In contrast, low-high and high-low clusters demonstrated a negative spatial association.

Finally, following Emrich and Cutter (2011), we employed a bivariate mapping technique using ArcGis® 10.6 by ESRI to spatially visualize where the social vulnerability scores and wildfire risk categories for each municipality coincide. For visualization, we grouped wildfire risk and social vulnerability scores into three broader classes: ´low´ (low and very low categories), ´moderate´ (including only the moderate category), and ´high´ (high and very high categories).

Results

Spatial pattern of social vulnerability

After performing PCA, five components were extracted, which jointly captured 73% of the variance, and each rotated component explained between 10% and 27% of the total variance. We obtained a value of 0.70 for the Keiser–Meyer–Olkin (KMO) test and a significant statistical Bartlett's test of sphericity, which confirmed that the sample was adequate for PCA.

Table 2 shows the component labels, percentage of the variance explained, and the drivers included in each component and their loadings. These five components are labeled 'socioeconomic status', 'social dependent (unemployed and disabled) population', 'household unit characteristics', 'education and health services', and 'socio-cultural institutions'. The first component, socioeconomic status, explained 27.17% of the total variance and included the percentage of the age-vulnerable population, children (under 5 years), and elderly (64 years or older) as well as aspects that capture the availability of financial resources of the community, all with a negative relation with social vulnerability: compound annual population growth rate, gross disposable income per capita, population with the highest tax base interval (greater than 60,101 €) declared in the annual income tax, which represents 3.5 times the average tax base declared in the region, and employment in the tertiary sector. The second component, a social-dependent population, accounted for 12.21% of the total variance. It included three variables: the unemployment rate (the number of unemployed in each municipality divided by the number of persons aged 16 to 64 in the municipality), people with physical or mental disabilities, and people receiving non-contributory State pensions (i.e., means-tested government payment for people who do not qualify for a State pension), all of which have a positive relation with social vulnerability. The third component, household unit characteristics, represented 12.08% of the total variance. It comprised the average number of people per household and the percentage of unoccupied housing units. The fourth component, education and health services, explained 11.54% of the total variance. This component captured access to education and health services measured as the teacher-student ratio (the number of teachers working in the municipality divided by the number of inhabitants between 4 and 19 years old in the municipality) and the number of people working in primary health care per inhabitant, respectively. Finally, the fifth component, socio-cultural institutions, accounted for 10.20% of the total variance. It represented access by households to sanitary, social, and leisure-hospitality facilities, with a net negative contribution to social vulnerability.

Figure 1 shows the spatial distribution of social vulnerability scores in the region. Based on the z-scores obtained, of the 313 municipalities, 42 (13%) were classified as having a very low social vulnerability, 67 (21%) low, 110 (35%) moderate, 38 (12%) high, and 56 (18%) very high. The municipalities labeled as least vulnerable (< -1) are mostly located along the Atlantic coast and include the main urban centers, such as A Coruña, Santiago de Compostela, Pontevedra, Vigo, Lugo, and their neighboring municipalities. Very high vulnerability scores (>1) are located in the interior of the region, mainly located in the provinces of Pontevedra and Ourense, near the border with Portugal. The global Moran's I statistic shows that these social vulnerability scores are spatially clustered (z-score= 0.52, p-value < 0.001).

Spatial coincidence of high social vulnerability and wildfire risk

The Kruskal-Wallis test showed statistically significant differences in the vulnerability scores by burned area categories (χ^2=33.739, df=4, p=0.000), i.e., higher social vulnerability scores are found in those municipalities with a higher proportion of burned area for the period 2010-2018 (Figure 2). However, we identified no statistically significant differences in social vulnerability scores by the number of wildfires per ha in the municipality over the same period (χ^2=4.040, df=4, p=0.401). Non-parametric hypothesis testing was used because vulnerability scores are more centrally distributed than a standard normal distribution, leading to the rejection of the normality hypothesis, according to the Lilliefors test (D=0.053 p=0.03) (Lilliefors 1967).

Table 3 shows that almost one-third of the municipalities in Galicia present high vulnerability scores (>1), which concentrates just 5% of the population and 15% of the buildings, 33% of the total number of wildfires, and 51% of the burned area in the studied period. High exposure to wildfire risk, as measured by burned area per ha (> 0.04), is highlighted by the fact that 125 (40%) municipalities are in this category, where 47% of the population live and where 40% of the total number of buildings of the region are located. In fact, these municipalities registered about 60% of the total number of wildfires, burning nearly 90% of the total burned area during the study period.

The bivariate local Moran's statistic between the social vulnerability scores and percentage of burned area per ha shows the presence of a statistically significant, positive spatial correlation (z-score= 0.226, p-value < 0.001), and a weaker positive spatial correlation with the number of wildfires per ha (z-score= 0.127, p-value =0.007). Therefore, burned area was chosen to visualize the relation between wildfire risk indicators and social vulnerability in the region. The LISA cluster map shows a significant local association between the percentage of burned area and vulnerability scores, with a p-value < 0.05 (Figure 3). High vulnerability and high wildfire risk areas are located in the interior of Pontevedra (municipalities belonging to O Condado, A Paradanta, and Vigo counties) and in Ourense province (municipalities belonging mostly to Baixa Limia, Verin, and Viana counties). Low vulnerability and low wildfire risk municipalities are located in the north of the region, in A Coruña and Lugo.

Figure 4 and Table 3 further illustrate the spatial coincidence of social vulnerability and wildfire risk. High values for vulnerability and wildfire risk are present in nearly 20% (59) of the municipalities, located in the southeast of Pontevedra and in nearly half of the municipalities of Ourense. These are low-density populated areas (16.5 people/km^2). A similar percentage, 17% (54) of the municipalities but where 23% of the total population resides, demonstrate low levels of social vulnerability and low wildfire risk, mainly located in A Coruña county and its surroundings, and Mariña counties in the North of the province of Lugo. Interestingly, 12% (36) of the municipalities are classified as having low social vulnerability scores but high wildfire risk. These municipalities are mostly concentrated along the Atlantic coast, and 36% of Galicia's population lives in these municipalities, registering the highest-population density (348 people/km^2) in the region.

High wildland-urban interface communities and social vulnerability

About 58% of the total population lives in municipalities with very high WUI presence (>26%), which have high population density (on average 556 inhabitant/km^2). The bivariate local Moran's statistic shows a positive spatial correlation between the proportion of WUI and the number of wildfires per ha (z-score= 0.212, p-value < 0.001) and negative spatial correlation between the proportion of WUI and burned area per ha (z-score= -0.068, p-value < 0.001). Municipalities with very low WUI presence (i.e., <7.8% of land area in the municipality) registered 50% of total burned area in the period studied, in contrast to those with very high WUI presence (>26% land area in the municipality), comprising just 9% of total burned area. This analysis also shows a significant negative spatial correlation between social vulnerability scores and the proportion of WUI in the municipality (z-score= -0.348, p-value < 0.001). The negative relationship is confirmed by the significant differences in social vulnerability scores across different category levels of WUI (χ^2=86.781, df= 4, p=0.000), also illustrating that higher vulnerability scores are registered in municipalities with a lower presence of WUI (Figure 5). Thus, just 10% of the total WUI is located in high vulnerability-high risk areas, while low vulnerability-low risk areas comprise 23% of the total WUI area of the region (Table 3). In fact, 47% of the WUI in the region is in municipalities with low social vulnerability. We found only 7 municipalities belonging to high vulnerability-high risk areas with a high WUI presence (>15.7% of the land area in the municipality), all located in the south of the region, in forest districts XI- O Ribeiro-Arenteiro (municipality of Maside), XII- Miño-Arnoia (municipalities of A Merca, Paderne de Allariz, and A Peroxa), and XVII-O Condado-A Paradanta (municipalities of Arbo, A Cañiza, and As Neves).

Finally, it is notable that the highest variability of social vulnerability scores is also registered for municipalities with very low presence of WUI (M=0.55, SD=1.15), in contrast to the lowest variability found in those with very high proportion of WUI (M=-0.84, SD= 0.56). This WUI-related distinction implies that there is greater homogeneity in social vulnerability among more urbanized municipalities, where WUI occupies the highest percentage of their total area.

Discussion

In this study, we identified specific locations where social vulnerability and wildfire hazard coincide spatially in the Spanish region of Galicia, a landscape with among the highest rates of wildfire in Europe (San-Miguel-Ayanz et al. 2013). We identified significant coincidence between social vulnerability and high wildfire risk, consistent with recent research findings in different areas of the United States (Gaither et al. 2011; Poudyal et al. 2012), Australia (Akter and Quentin 2021), and Portugal (Nunes and Lourenço 2018). In Galicia, municipalities with high vulnerability and high risk of wildfire were found to be mainly located in the rural Southeast.

In our analysis, we developed a social vulnerability index in the studied region that was consolidated into a few uncorrelated factors representing the social-economic dimensions of vulnerability. The factors included the proportion of the elderly population and of the elderly living in single-person households, and whether communities were characterized by low population density, economic disadvantage (i.e., a high proportion of the population receiving income support from the government), and limited access to health and socio-cultural services. Results also validate findings from previous studies, showing that the elderly lack self-sufficiency, the capacity to quickly react to the threat of a wildfire, and the economic means required for applying mitigation measures (Cutter and Emrich 2006, Palaiologou et al. 2019). Population growth is negatively related to vulnerability, as high population growth is often associated with prosperous regions in Spain (Martín et al. 2017). The vulnerability score also includes the percentage of workers in the tertiary sector, since there is a correspondence between progress in rural areas and a higher density of companies and self-employment in the services sector in Galicia (Peón et al. 2020). In areas where the population has higher financial resources, there is a greater ability to mitigate damages in the case of a wildfire, applying prevention and recovery measures, even in the absence of public provision of emergency aid or financial assistance (Davies et al. 2018). Social-dependent populations were found to be more vulnerable, as people who are dependent on income support and social services due to unemployment or because they have physical or mental disabilities will require additional support in the event of wildfire (Cutter et al., 2003). We found that areas with larger households on average were associated with lower vulnerability, a finding potentially explained by the presence of stronger social networks, which can increase a household's ability to face and recover from a disaster (Tierney 2006, Grainger et al. 2021). In addition, in rural areas, one-person households could involve the elderly living alone, who are considered physically and socially vulnerable to wildfires because they face health and economic issues and assistance needs (Hung et al 2016, Sung and Liaw 2020). The vulnerability score also accounts for population abandonment in Galicia, a measured by the percentage of unoccupied housing units (Brouard–Sala et al. 2018), which is associated with social vulnerability to wildfires because absentee property owners are less willing to implement prevention and mitigation measures (Paveglio et al. 2009, Oliveira et al. 2020). The negative effect of access to education and health care on vulnerability are based on (i) the role of education on vulnerability through its relationship to participation rates in wildfire risk education programs (Champ et al. 2013) and its association with both compliance with wildfire prevention measures and evacuation instructions during an emergency (Cutter et al. 2003); and (ii) the importance of health care during the recovery stage (Fatemi et al. 2017) and its role as attribute of social resilience (Maclean et al. 2014). Access to socio-cultural institutions also has a net negative effect on social vulnerability because of the broad array of services that these institutions can provide in response to any hazard (Fatemi et al. 2017).

All of these dimensions were consistent with recent demographic shifts toward an older, lower-wealth population that have been evident in rural Galicia in recent decades, i.e., the emigration of younger residents has resulted in an older resident population (López-Iglesias, 2019). Residents of communities in such rural areas now find themselves in a landscape of accumulating hazardous fuels (Damianidis et al. 2021), making them more favorable to wildfire. Most (76%) of the municipalities with high social vulnerability and high wildfire risk have low levels of WUI; that is, high-WUI municipalities generally have lower social vulnerability. Therefore, our findings are consistent with previous studies, which found that non-WUI settlements concentrate a higher proportion of low-income populations (Lynn and Gerlitz 2006) and a higher number of subsidized households (Gabbe et al. 2020), i.e., they are more socially vulnerable, by definition. These WUI areas tend to be physically and economically connected to urban settlements that are relatively wealthy and therefore less vulnerable (Peón et al. 2020). Nevertheless, such high-WUI communities face grave risks from catastrophic wildfire events, due to accumulated hazardous fuels, an exposed housing infrastructure, and relatively high human population densities. Our results also show that there is a large share of the population of Galicia in this situation: 11% of municipalities in the Atlantic high-WUI urban nexus, whose population comprises 36% of the region's total population, face high wildfire risk. The higher risk of ignition found in these areas, however, contrasts with the relatively lower risk of wildfire spread in these landscapes, because wildfires are detected sooner after ignition, suppression resource access is easier, and more suppression resources are applied to fires when they occur (e.g., Calviño-Cancela et al. 2016, Oliveira et al. 2018). Finally, it is worth noting that seven municipalities identified with high social vulnerability and high wildfire risk are also high-WUI communities. For example, one such municipality is As Neves, in Forest District XVII, where 48% of its area was burned by wildfire in October 2017, and nearly all its population (98%) lived within 1 km of the burn area at the time (Chas-Amil et al. 2020).

A shortcoming of this study is that it provides a static picture, based on the socio-economic conditions measured during recent history. These results may be different using older periods of reference or in the future, as conditions change. For example, future land use changes, such as those leading to increased WUI (e.g., Theobald and Romme 2007), and changes in climate (IPCC 2021) could alter the picture of wildfire vulnerability throughout the region.

Furthermore, it is well-recognized that composite indicators, such as the social vulnerability scores used in this work, are useful for summarizing complex, multi-dimensional realities, and so they can be criticized for being an overly simplified characterization of societal vulnerabilities (OECD 2008). Alternative qualitative methods and expert opinions have been suggested to improve variables selection (Spielman et al. 2020), which could give greater attention to factors associated to sensitivity and adaptive capacity. Still, we contend that the index we developed is potentially useful to policymakers because it identifies those locations in the region where efforts to improve the preparedness of the most vulnerable population could be focused, resulting in increased social resilience to wildfires.

Conclusions

There is an increasing acknowledgment of the importance of addressing the socioeconomic determinants of vulnerability in communities that could help to prepare more effectively for wildfires, leaving these communities better equipped to cope with and recover from their adverse effects (Coughlan et al. 2019). Mapping the distribution of wildfire risk and social vulnerability is a key step towards spatially targeting where policy actions are most needed to achieve wildfire-resilient landscapes. Our findings show that communities highly exposed to wildfires which tend to be most socially vulnerable are often located in rural areas, and our results suggest that targeted policy actions for mitigating the social vulnerability in these areas could include addressing the lack of financial resources, the social isolation of elderly people living alone, and the existence of a weak local health care infrastructure. Such actions may contribute to the reinvigorating of rural economies and settlements, which indirectly could also help to limit accumulation of hazardous fuels in these landscapes and therein the likelihood and impacts of wildfires.

This paper also specifically addressed vulnerability in the WUI, which is emerging as an active area for new research and development (Coughlan et al. 2019). Our results showed that municipalities with the highest proportion of their area under the WUI have high wildfire risk but low social vulnerability. Nevertheless, in these densely populated landscapes, uncontrolled wildfires can have serious consequences for lives and properties, highlighting the potential value of efforts to further strengthen emergency response capacities, including introduction of communication policies that bolster plans and systems to facilitate evacuations.

Land use planning that addresses housing development in fire-prone areas and the design of infrastructure and their environments offers other avenues to reducing the impacts of catastrophic wildfires (Pastor et al. 2020, Vacca et al. 2020). Our analysis helps to identify places in the landscape with high wildfire potential based on historical data where such actions may provide the highest benefits. The diversity of the spatial linkages between vulnerability, wildfire risk, and WUI presence found in this study offers a new perspective for policymakers, emphasizing that a wide range of actions may be needed to effectively address wildfire related socioeconomic concerns among the socially vulnerable.

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Table 1. Variables used in the development of the social vulnerability index and to characterize wildfire risk and wildland-urban interface presence and their mean, standard deviation, and minimum and maximum values.

Variable	Mean	Std. Dev.	Min.	Max.
Gross Disposable Income per capita (€)	12,590	2095	5,389	22,959
% population with the highest tax base interval (greater than 60,101 €) declared in the annual income tax	1.05	1.18	0.00	8.71
Number of teachers working per inhabitants between 4 and 19 years old.	0.1	0.07	0.00	0.57
% adults receiving a non-contributory State pension	1.81	0.81	0.46	5.13
% population with physical and mental disability of 33% or higher	9.02	2.36	4.62	19.66
% unemployed population	9.54	2.57	4.09	20.59
Number of people working in primary health care per inhabitant	0.003	0.0016	0.00	0.013
% sanitary and social centers	0.11	0.10	0.00	1.27
% employed in the tertiary sector	62.86	9.18	36.31	86.81
% of leisure-hospitality buildings	0.26	0.33	0.00	4.19
% population under 5 years or 64 years or older	36.24	8.10	17.45	55.99
Compound annual population growth rate in the last 20 years (%)	-0.99	1.22	-3.49	3.37
Average number of people per household	2.93	0.39	2.20	4.20
% unoccupied housing units	18.71	7.21	0.68	40.62
Number of wildfires per hectare	0.011	0.009	0.00	0.059
Burned area per hectare (%)	7.2	11.8	0.00	74.7
% of wildland-urban interface	17.0	12.0	1.4	65.2

Table 2: Component labels, percent of variance explained, dominant variables, and component loadings for the social vulnerability index.

Component label	% of the variance explained	Nº of drivers	Dominant variables	Loadings
Socioeconomic status	27.17	5	- Compound annual population growth rate (%)* - % population under 5 years or 64 years and older - % population earning over 60,101 € declared in annual income tax* - Gross Disposable Income per inhabitant (€) * - Employment in the tertiary sector (%)*	0.893 0.871 0.847 0.823 0.597
Social dependent population	12.21	3	- Unemployment rate (%) - % population with any disability of 33% or higher (%) - People receiving State pension (non-contributory) (%)	0.766 0.726 0.582
Household unit characteristics	12.08	2	- Average number of people per household* - % unoccupied housing units	0.803 0.680
Education and health services	11.54	2	- Number of teachers working in the municipality per inhabitant between 4 and 19 years old* - Number of people working in primary health care per inhabitant*	0.891 0.874
Socio-cultural Institutions	10.20	2	- % sanitary and social buildings* - % leisure-hospitality buildings*	0.849 0.792

* The directionality of the standardized variables was reversed before principal component analysis.

Table 3. Number of municipalities, population, buildings, wildfire count, total burned area, and WUI total area according to types of association between social vulnerability and wildfire risk.

	Municipalities (%)	Population (people/km^2)	Number of buildings	Number of wildfires	Burned area (ha)	WUI area (ha)
Low vulnerability-Low risk	54 (17%)	628,140 (127.5)	309,063	3,077	3,492	87,559
Moderate vulnerability-Low risk	55 (18%)	200,307 (38.5)	208,677	2,594	3,714	66,898
High vulnerability-Low risk	16 (5%)	16,184 (16.4)	26,561	372	615	8,576
Low vulnerability-Moderate risk	19 (6%)	422,937 (197.9)	122,590	2,181	4,983	32,493
Moderate vulnerability-Moderate risk	25 (8%)	141,074 (41.8)	127,090	2,348	8,045	38,542
High vulnerability-Moderate risk	19 (6%)	32,632 (24.1)	48,003	1,166	3,224	14,677
Low vulnerability-High risk	36 (11%)	963,762 (348.0)	285,803	4,497	27,315	61,903
Moderate vulnerability-High risk	30 (10%)	209,785 (59.2)	138,925	4,329	51,044	35,303
High vulnerability-High risk	59 (19%)	86,998 (16.5)	140,453	7,882	97,607	39,226
Total	313	2,701,819 (91.4)	1,407,165	28,446	200,040	385,177

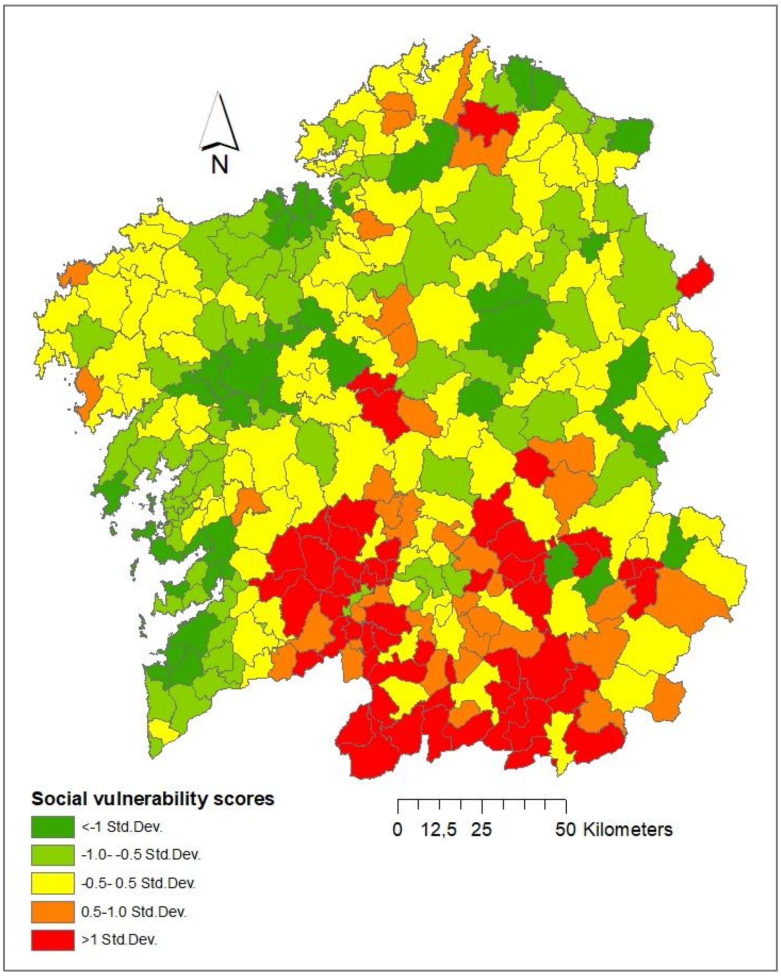

Figure 1: Social vulnerability scores in Galicia's municipalities. Less than -1.0 standard deviation indicates a very low social vulnerability, between -1.0 and -0.5 low, between 0.5 and 1.0 high, greater than 1.0 very high, and between -0.5 and 0.5 a moderate social vulnerability.

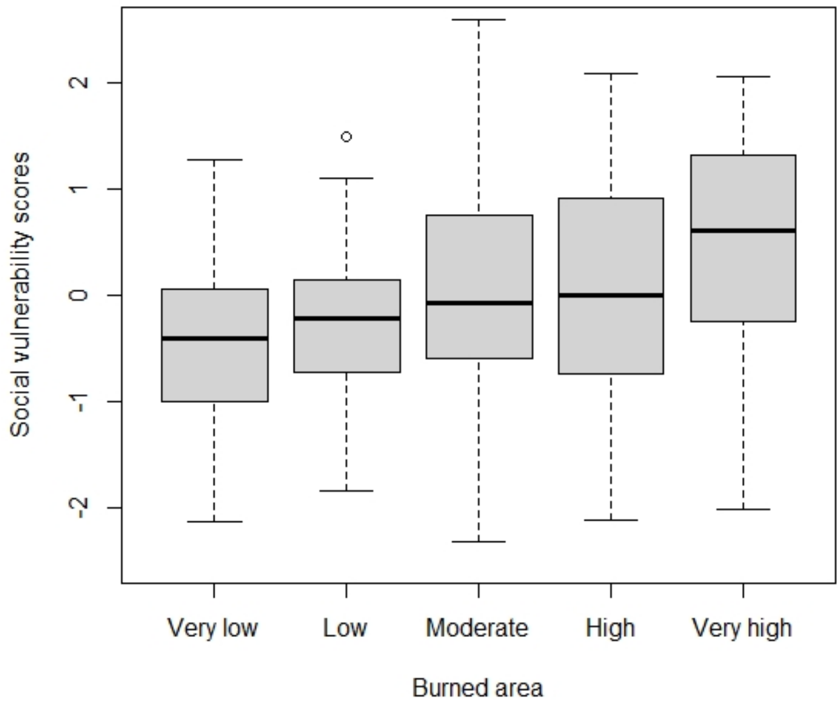

Figure 2. Social vulnerability scores by percentage of burned area in the period 2010-2018. Boxes extend from the 25th and 75th percentiles, with medians in the inner horizontal line, and whiskers show the maximum and minimum value excluding outliers.

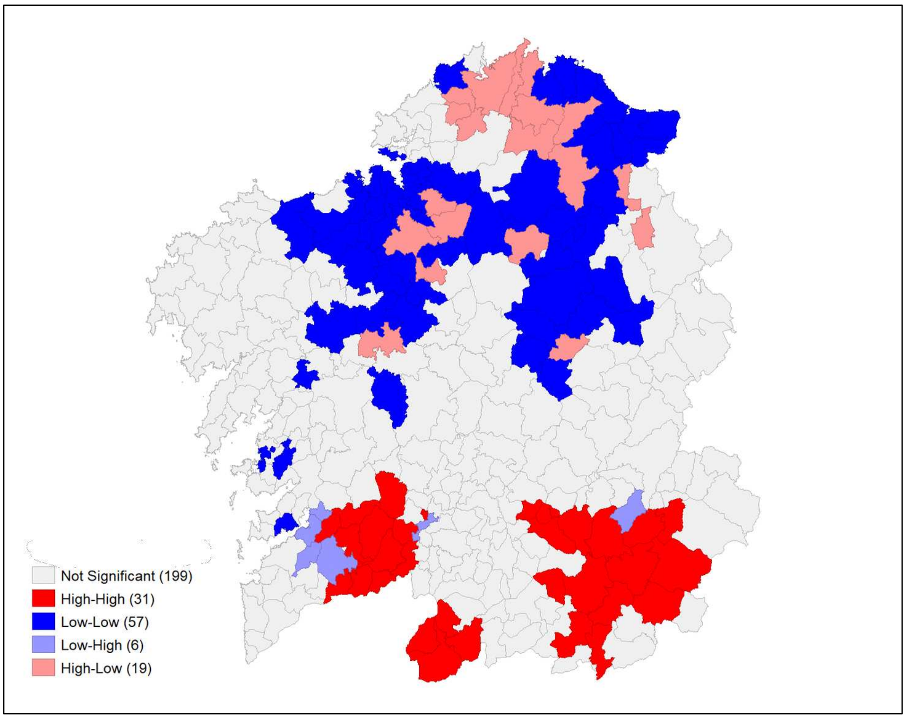

Figure 3. LISA map resulting from the computation of the bivariate local Moran's statistic showing the spatial local association between social vulnerability scores and burned area per ha. Red color indicates hotspots with high social vulnerability scores and high burned area per ha, dark blue clusters show coldspots with low social vulnerability scores and low burned area per ha. Gray areas present no statistically significant spatial association.

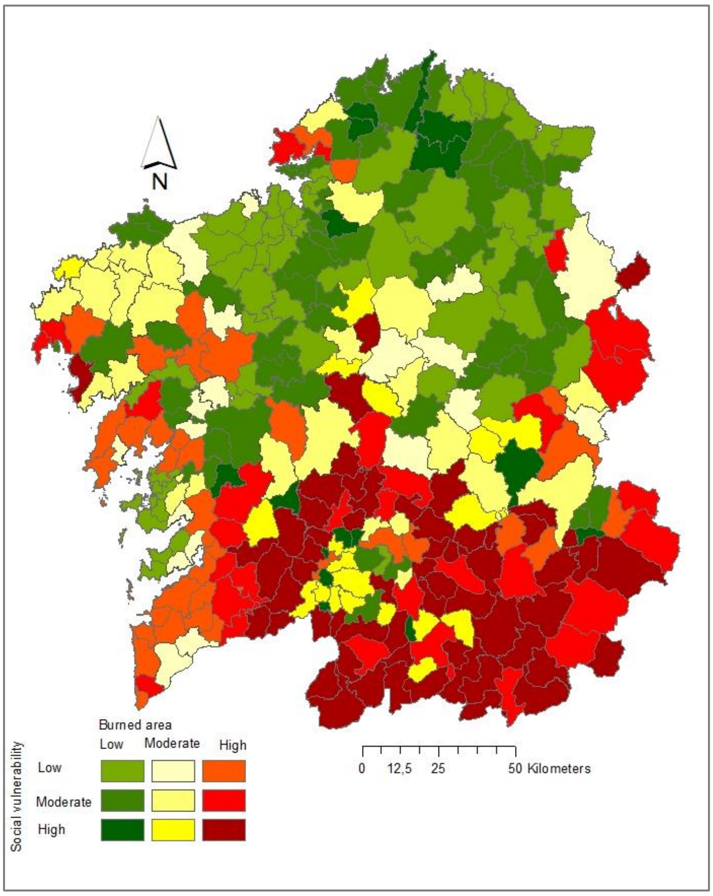

Figure 4. Bivariate map depicting social vulnerability scores and burned area per total area of the municipality. Green, yellow and red distinguish across low, medium and high burned area as an indicator of wildfire risk. Within the wildfire risk level, color intensity increases as the social vulnerability score increases.

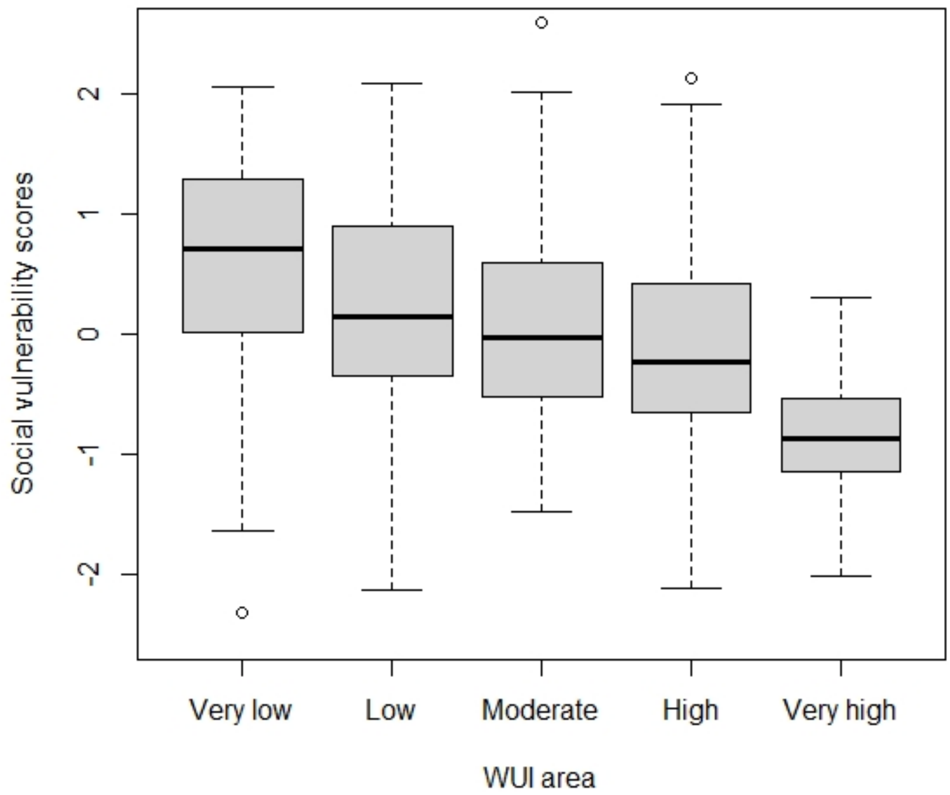

Figure 5. Social vulnerability scores by WUI area. Boxes extend from the 25th and 75th percentiles, with medians in the inner horizontal line, and whiskers show the maximum and minimum value excluding outliers.