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PLS-PM analysis of forest fires using remote sensing tools. The case of Xurés in the Transboundary Biosphere Reserve

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ABSTRACT

Forest fires have environmental, social and economic impacts in many areas. Various factors related to territory directly influence both the number and the surface area of each fire. The link between different variables (climate, social and environmental) in the risk of fire and in the characteristics of fires is studied here through Partial Least Squares - Path Models. In addition, images from the Sentinel-2 sensor and geographic information systems are used to create a cartographic base of fires in the Transboundary Biosphere Reserve of Galicia and the Site of Community Importance of Xurés (Galicia) between 2015 and 2020. In all, seven variables are analyzed in this study area using the partial least squares-path modeling method: climate, topography, land use, type of environmental protection, the anthropogenic factor, fire defense, and fire data (severity and area). The parameters for each variable are used to obtain weights and thus determine the importance of each one. The areas where the problem of forest fires is greatest are those with the greatest environmental protection. Up to 31% of the surface area of the Natura 2000 Network was burned in the 6-year study period. Topography and land use are also shown to be relevant factors in the effects of forest fires in this territory. By contrast, higher population density and the development of infrastructures such as roads and water tanks mitigate the impact of fires. The problem of forest fires encompasses many variables that need to be studied. By contextualizing each study area as far as possible, specific measures to prevent and reduce damage can be drawn up.

1. Introduction

In the past few decades, forest fires have become a global environmental problem, and the trend in the fire regime has changed. Wildfires are becoming bigger and more severe (Miller et al., 2012). This leads to changes in ecosystems, thus further increasing the intensity of fires and changing the fuel models (Keeley and Pausas, 2019; Nagy et al., 2018). Those changes can also have socio-economic impacts and direct effects on health. This is a challenge not only for rural populations, but also for those in the wildland-urban interface, where the risk of fire increases (Calviño-Cancela et al., 2016; Pastor et al., 2020).

The causes of forest fires vary from one study area to another, with natural causes predominating in past centuries and in large forest ecosystems (Gromtsev, 2002; Mutch, 1970). However, in most areas of the world the main cause of fires today is human action (FAO, 2007), which makes designing a solution more complicated. Numerous studies point to the difficulty of finding solutions due to the large number of factors involved. Major factors include the local economy and the model of production and work (Balsa Barreiro and Hermosilla, 2013). Other factors are related more to the social customs of the population and the use of fire for different tasks, leading to a higher risk of negligence (Barreal and Loureiro, 2015; Marey-Perez et al., 2021). In Europe's Mediterranean countries, the human factor is behind far more wildfires (Martínez et al., 2009; Vilar et al., 2016) than lightning, the main natural cause, with a figure of approximately 5% (Vázquez and Moreno, 1998). In the northwest of Spain, specially in the study area, a large number of studies show the key factor of private ownership and the large number of small plots of land in forest fires (Fuentes-Santos et al., 2013; Marey-Pérez and Rodríguez-Vicente, 2009). This is in addition to the management of forest plots in areas with a high degree of environmental protection (Rodríguez et al., 2022).

Moreover, monitoring, characterizing, and zoning fires is an arduous task which requires a lot of field work, technical and human efforts and a great deal of time. Remote sensing and geographic information systems (GIS) can help monitor and prevent wildfires and also serve as a fire management support tool (dos Santos et al., 2021; Mahdavi, 2012;

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Mallinis et al., 2018). In this sense, space programs offer valuable, freely accessible information through satellite imagery. Among the most widely used sensors are Landsat (Vega-García and Chuvieco, 2006), MODIS (Kaufman et al., 1998), and Sentinel (Novo et al., 2020a; Picos et al., 2019). The different spatial and temporal resolutions of the sensors determine which is the best choice for research. Other, privately owned satellites such as the Deimos-1 sensor have different costs, or need further assessment in different ecosystems, (García-Llamas et al., 2019). In addition, Light Detection and ranging (LiDAR) is also commonly used to characterize the main variables involved in forest fires (Novo et al., 2020b). Also using remote sensing technologies together with field work makes it easier to find preventive actions in risk areas.

In addition, statistical modeling can be useful for analyzing the multiple causes and factors involved in environmental problems. Combined with GIS technology, spatial analysis helps to locate areas for action (Sun et al., 2015). This can simplify decision-making. One of the most widely used models is Partial Least Square-Path Modeling (PLS-PM), originally used in social sciences (Chin et al., 2003). Numerous environmental studies use this statistical model to deal with large field databases and characterize the different variables (Fu et al., 2015; Oliveira et al., 2019; Sanches Fernandes et al., 2018). In the field of forest fires, studies focus mainly on ecological issues of soil regeneration (Cécillon et al., 2009; Wang et al., 2022). The possible causes of forest fires are relegated to the background because of how difficult they are to study (Ganteaume and Jappiot, 2013). We can find no studies that analyze the possible causes of forest fires and the influence of the many factors involved through PLS-PM. Therefore, the opportunity arises to apply a model that has obtained positive results in other fields, applying it this time to the field of forest fires. This novel study aims to use the PLS-PM method to analyze the causes of a problem with numerous variables from different fields such as environmental, sociological, ecological and cultural. The aim of the study is to determine the influence of the causes acting in the area where forest fires occur, and thus determine the effectiveness of least squares statistical models applied to the field of forest fires. This study is carried out using GIS tools, by means of a mathematical analysis and through an innovative and different point of view for areas where these disturbances are recurrent, have multiple causes and are difficult to resolve, opening up the possibility of relating numerous data and understanding their impact.

2. Materials and methods

2.1. Study area

The study area is in the province of Ourense (Galicia) in northwestern Spain (Fig. 1). It has a total surface area of 683 km^2 and includes the Spanish part of the Geres-Xurés TBR and the Site of Community Importance (SCI). In addition to these two, other highly important environmental protection areas also lie within the study area, such as the Galicia Xurés Natural Park and the Special Bird Protection Area (SBPA). The area is in a biogeographical region with a climate that is between Atlantic and Mediterranean. High temperatures in the summer months (average maximum 20.6 °C in August, (Pérez-Alberti, 2022)) make this natural park one of the most susceptible to fire in Galicia. At the turn of the century the local population numbered 15,000, though that figure has now dropped to 10,000 (Xunta de Galicia, 2021a, 2021b). The border with Portugal is marked by the Laboreiro (west), Xurés (center) and Pena (east) mountain ranges. These mountains, made up of large granite rocks, are between 1200 and 1500 m in altitude. The reserve is made up mainly of pastures, scrubland and rocky areas. It contains a great variety of flora, including several endemic species such as *Prunus lusitánica* and *Iris boissieri*. There are also invasive species such as *Acacia de albata*, which proliferate and spread due to forest fires (Lorenzo et al., 2010). There are also numerous endemic aquatic species (such as *Barbus*

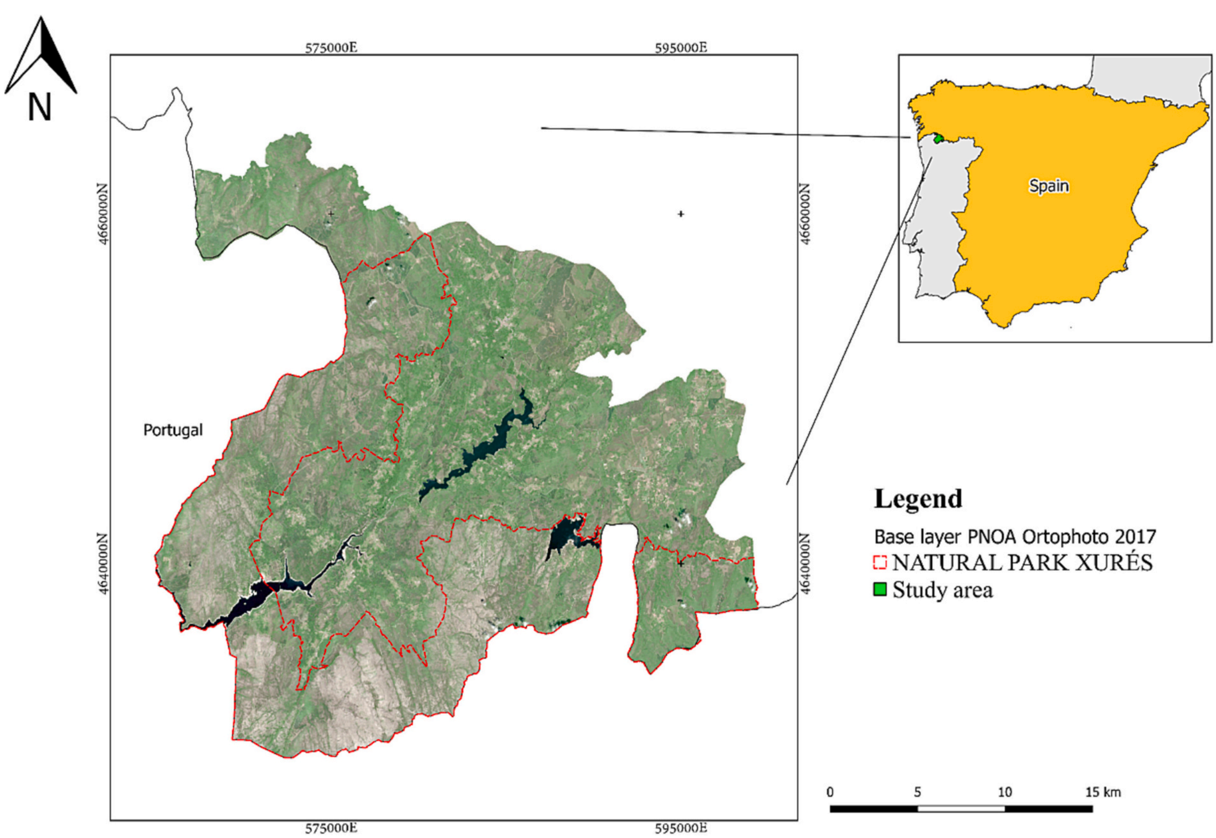

Fig. 1. Location of the study area. Coordinate system ETRS89/UTM zone 29 N.

bocagei and *Pseudochondros tomaduriense*, among others) and numerous insects of interest. In all there are 30 species of amphibians and reptiles and close to 40 species of mammals, with bats and wildcats standing out as particularly endangered (Domínguez et al., 2012). Wild boar, roe deer and even wolves abound in the area, maintaining the balance between predators and other wildlife. The Pyrenean mountain goat was reintroduced in 1992, and by 2012 there were around 600 individuals (Herrero et al., 2021). The SBPA is home to over 100 predatory, Mediterranean, and mountain species including the golden eagle, the peregrine falcon, and the goshawk among many others (Domínguez et al., 2012). Taking into account that the area's agricultural, livestock, and forestry systems are highly rural and traditional in nature, numbers of cattle and ungulates are high throughout the year. Due to the important biodiversity of flora and fauna, the climatic conditions and the orography, this region has important starting conditions where forest fires can be a problem. In addition to this, there is a general trend of depopulation of the countryside. Historically, forest fires in the study area have been very numerous, as reflected in the reports of the Spanish Ministry of the Environment for decades (Ministerio para la Transición Ecológica y el Reto Demográfico, 2022). Since 2001 until now there have been >1500 fires, although >70% of them have an area of <5 ha. The trend is decreasing in terms of the number of ignitions, unlike the surface area affected, with very accentuated years, such as 2005 and 2011 with >3000 ha affected per year (Rodríguez-Jiménez et al., 2021).

2.2. Dataset preparation

This study analyzes the fires that occurred in the study area between 2015 and 2020. Various fire-related parameters are analyzed (Table 1), such as anthropogenic and management factors, and their links with fires are studied through Partial Least Square- Path Models (PLS-PM). The database is drawn up from various sources of information (Table 1). The physical variables of the natural environment are calculated from the Digital Terrain Model (DTM) available from the Spanish National Geographical Institute (IGN). The resolution used for the study area is 25 m, in ASCII format. Climate data is obtained from the meteorological stations belonging to the State Meteorological Agency (*Muiños*) (*España, M. para la transición ecológica y reto demográfico. G. de,* 2021) and to MeteoGalicia (*Calvos*, *Cequeliños, Entrimo, Gandarela, Lobios, Xinzo, Xurés*) (Xunta de Galicia, 2021). Three territorial variables are considered, all drawn from the information system on land occupation in Spain (SIOSE) (de España, 2016). For the study area the information on land occupation is for 2016, making it the most up-to-date official version in Galicia, with a higher level of detail than Corine Land Cover. The anthropogenic variables considered are distances calculated from buffers created around towns, roads and the network of water points of the fire-fighting system (Xunta de Galicia, 2021a, 2021b). These water points also refer to rivers and reservoirs where water loading can take place, thus increasing the relationship with hydrological factors, together with rainfall and relative humidity, collected by weather stations. Under the Master Plan for the Natura 2000 Network in Galicia, the protection areas in the study area are grouped under two headings, according to the conservation and protection area. There are three levels of protection in Natura 2000 Network in Galicia. These are the first and second level of protection respectively. The protection area includes territories with a very high conservation value, while the conservation area contains territories with high and medium conservation values, especially humanized. Finally, the severity and the surface area of fires are derived directly from the dataset database, calculated from the Relativized Burn Ratio (RBR) (Parks et al., 2014) following the methodology set out in Subsection 2.3.

2.3. Forest fire detection

Fires are mapped from the Sentinel-2 sensor in the months of greatest fire activity for each year, from July to October. In certain years such as 2017 and 2019, images prior to July are analyzed to capture the most important fires. The Sentinel-2 mission is part of the Copernicus Earth observation program, with twin satellites Sentinel 2A launched in 2015, and Sentinel 2B in 2017. Sentinel-2 carries multispectral imaging instruments on board. The spatial resolution for the output product chosen is 20 m, due to the spectral bands using the most usual indices for mapping burned areas and their severity. Fires are detected through the application of the RBR. This index is calculated from the Normalized Burn Ratio (NBR) (Key and Benson, 2005), using Band 8A and Band 12 in the pre-fire and post-fire images following Eq. 1. The post-fire images

Table 1
Variables measured in the partial least squares analysis, latent variable to which they belong, a short description of each one and the units of measurement. Those figures for which no units are given are treated as % of the total surface area of the fire affected.

Latent variables		Measured variables	Units	Description
		MAX_ALTITUDE MED_ALTITUDE	*m*	Maximum and average altitude of the area affected by the fire. Obtained from the DTM in Qgis v3.16
		MAX_SLOPE MED_SLOPE	%	Maximum and average slope of the area affected by the fire. Obtained from the DTM in Qgis v3.16
Environmental factors	Climate	RH PRECIPITATION TEMPERATURE	% *mm* °*C*	Data obtained from the interpolation of the meteorological stations in the area from May to October.
		MAX_SEVERITY MED_SEVERITY		Maximum and average severity of the area affected by the fire. Between 0.25 and 1
Fire factors		AREA	*ha*	Surface area affected by the fire.
Territorial factors		%_FOREST %_SCRUB %_ROCKY	% % %	% of total surface area affected. Data from SIOSE
Environmental Protection factors		%_CONSERV_AREA	%	% of surface area affected by the fire in the Conservation Area. RN2000 zoning. (Environmental protection plan)
		%_PROTEC_AREA	%	% of surface area affected by the fire in the Protection Area. RN2000 zoning. (Environmental protection plan)
Anthropogenic factors		%ROAD_ < 100mts	%	% of surface area affected by the fire <100 m from the road
		%ROAD_ > 1000mts	%	% of surface area affected by the fire >1 km from the road
		%_500mts_SETTLEMENT	%	% of surface area affected by the fire <500 m from a village
		%_ > 3000mts_SETTLEMENT	%	% of surface area affected by the fire >3 km meters from a village
	Fire defense	%%WATERPOINT_ < 500mts %WATERPOINT_ < 1000mts %WATERPOINT_ < 1500mts %WATERPOINT_ < 2000mts	 % % %	% of surface area affected by the fire at the established distance from a water point

Table 2
Date and percentage of clouds in the satellite images used for the detection of the fire.

Year	Data Pre-fire	Cloud cover (%)	Data Post-fire	Cloud cover (%)
2015	15/07	8,6%	25/07	0,0%
2015	25/07	0,0%	15/11	4,2%
2016	20/05	3,7%	18/08	5,4%
2016	18/08	5,4%	25/01 ('17)	2,3%
2017	25/01	2,3%	22/10	3,4%
2018	12/09	0,1%	07/10	0,6%
2019	10/01	0,1%	30/04	6,3%
2019	30/04	6,3%	22/10	0,5%
2020	18/07	0,0%	11/10	0,0%

are selected on the basis of the changes observed thanks to the *Sentinel Playground viewer*. Local news about forest fires also helped us to select post-fire images:

$$NBR = \frac{B8A - B12}{B8A + B12} \quad (1)$$

Once the NBR is obtained the dNBR, which indicates the burnt surface area, is calculated following Eq. 2.

$$dNBR = NBRprefire - NBRpostfire \quad (2)$$

Lastly, RBR is calculated (Eq. 3) to obtain the map of the severity of the burnt areas.

$$RBR = \frac{dNBR}{NBRpre + 1.001} \quad (3)$$

The pre-fire and post-fire images used were a total of 15, from 2015 to the end of 2020. This covers a sufficient period of time to detect the most important fires. The percentage of clouds in all of them is <9% (Table 2).

2.4. Principal analysis: partial least squares - path models

The Partial Least Squares (PLS) algorithm developed by Wold (Wold, 1966) seeks to model causal paths via so-called latent variables (LV). The building blocks that make up the PLS regression models are the dependent and independent blocks. The number of LV and their trajectories are clearly defined in the PLS-PM, called the inner model. This inner model, also known as the structural model, is linked to the measured variables (MV) to make up the external model (Wold, 1980). The connections between LV are quantified through path coefficients in the inner model. For the external model, the connections between LV and MV are quantified with weights (Hair Jr et al., 2021). The coefficient of determination (R^2) represents the amount of variance in the dependent latent variable (called "endogenous"). This coefficient is obtained in every regression in the inner model. The independent latent, or "exogenous", variable has an influence on the endogenous latent variable represented by the path coefficients.

The Smart-PLS program (v3.3.5) analyzes PLS-PM and maximizes R^2 from the different weights of the parameters in the latent variables and their connections. Other models are created, but they contain variables that do not respond logically to the results. The interpretation of the weight of each variable depends on the coefficient obtained. The coefficients obtained range from −1 to 1. Extreme values represent a strong interaction or a greater weight, while values close to zero represent a lower weight and weaker interaction. The result for the endogenous latent variables is an R^2 from the score of the latent variables and the direct effect or path. For the scheme carried out, only the Natural Factors and Fire Factors variables have an R^2. This is the predicted score (PS), calculated from the sum of the product of the latent variable to which it is related and the path coefficient. For exogenous latent variables the measured score (MS) is calculated from the sum of the weights of each measured variable. According to Hoyle (1999), Garson (2016) and Moran et al. (2018), in a sample of 56 forest fires the maximum number of variables measured must be 5. Starting from this constraint, different models are tested in the Smart-PLS program. Mainly anthropogenic variables are selected, with those with no great relevance being discarded and those that have most weight included. The resulting model comprises 24 measured variables, represented by yellow rectangles, and 7 latent variables, represented in the model by blue circles (Fig. 2).

Each fire is associated with each of the variables studied from the different data sources. Altitude and slope are directly calculated in the free software QGis v3.16, using a DTM of the study area. Climate data is collected from the eight closest meteorological stations in the study area. Three of them (*Cequeliños, Gandarela, Xinzo*) are outside the study area, but are close to it and form part of its area of influence. These must be taken into account for a correct interpolation. Climate data for the whole area is interpolated via the Module Thin Plate Spline tool, using the SAGA library, for every year in the period studied. The annual mean value comes out of each daily mean value of the meteorological variable in the period studied in that year. Climate data for each year can be linked to the year in which each fire occurred. Moreover, a layer with information on land occupation is obtained and clipped to the area of interest. The main land uses in the study area are forest, scrub and rocky areas. These land uses are filtered to obtain the surface area affected by fires for each type of land. Finally, the layers with the settlements, roads, and water points of the fire system are used to produce buffers at different distances, and minimum and maximum distances for roads and settlements are selected. These buffers form polygons that enclose the main area with a set size around a geographical object. They are used to check the area of influence. The centroid of the settlement and the water point is the geographical object on which the buffer is created with a distance interval of 500 m. Only asphalted roads are selected, with buffers at distances of 100 m. This interval is smaller because the density of roads is higher than that of settlements or water points. The percentage of the fire surface area affected within that distance is calculated in QGis v3.16. The PLS-PM analysis takes only the minimum and maximum intervals for roads and settlements, and the minimum two kilometre distance from water points. Other measured distance parameters are discarded as they provide no new information.

2.5. Sensitivity analysis

In addition to the PLS-PM analysis, a sensitivity analysis is performed for multiple confounding factors, regardless of whether they linearly influence the treatment. In this way the robustness of the model is analyzed and the omitted variable bias framework is extended. The methodology of this analysis is followed according to Cinelli and Hazlett (2020). Sensitivity analyses in environmental models are important when analyzing the confusion matrix (Hazlett and Mildenberger, 2020; Pianosi et al., 2016) The analysis is performed for the model with all parameters included in the dataset, taking as benchmark covarities those related to hydrology, in this case factor "precipitation" and for the associated treatment the opposite climatic variable "temperature".

3. Results

3.1. Sentinel-2 burnt surface area

Based on the fires mapped in the working area, the dataset is formed with the 56 forest fires detected via Sentinel-2 (Fig. 3). In total, 12,500 ha were affected from 2015 to 2020. The fires range from 1 ha to 3266 ha (in the case of the largest fire, in 2017). 6 Large Forest Fires (> 500 ha) are recorded, but >50% of the fires mapped do not exceed 20 ha. The most frequent fire size mapped is 19 ha.

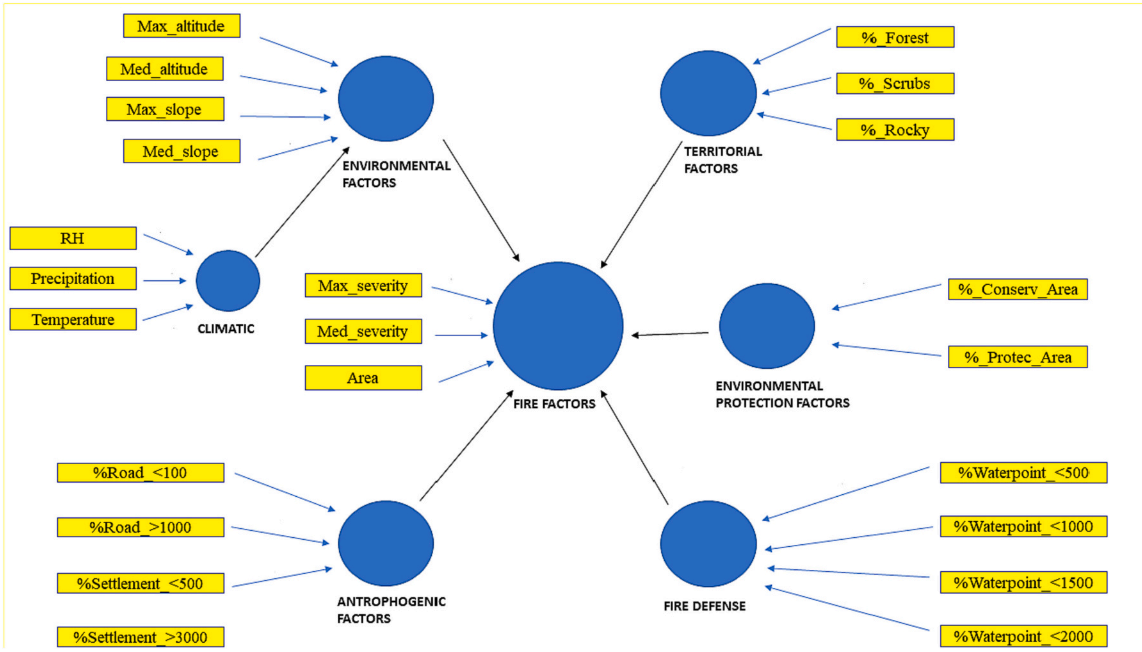

Fig. 2. Diagram showing PLS-PM. Yellow rectangles represent measured variables and blue circles latent variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Influence of factors on forest fires

The different factors analyzed influence forest fires to different extents, which can be observed via maps that relate several variables. For the influence of water points on fire spread (Fig. 4a), these maps show that there are fewer water points in the areas where the largest fires occur, towards the outside of the study area. In the interior, where fires do not exceed 20 ha, the network of water points is more extensive. It also coincides with the highest density of population and roads (Fig. 4b, c). The largest areas affected by forest fires are furthest away from paved

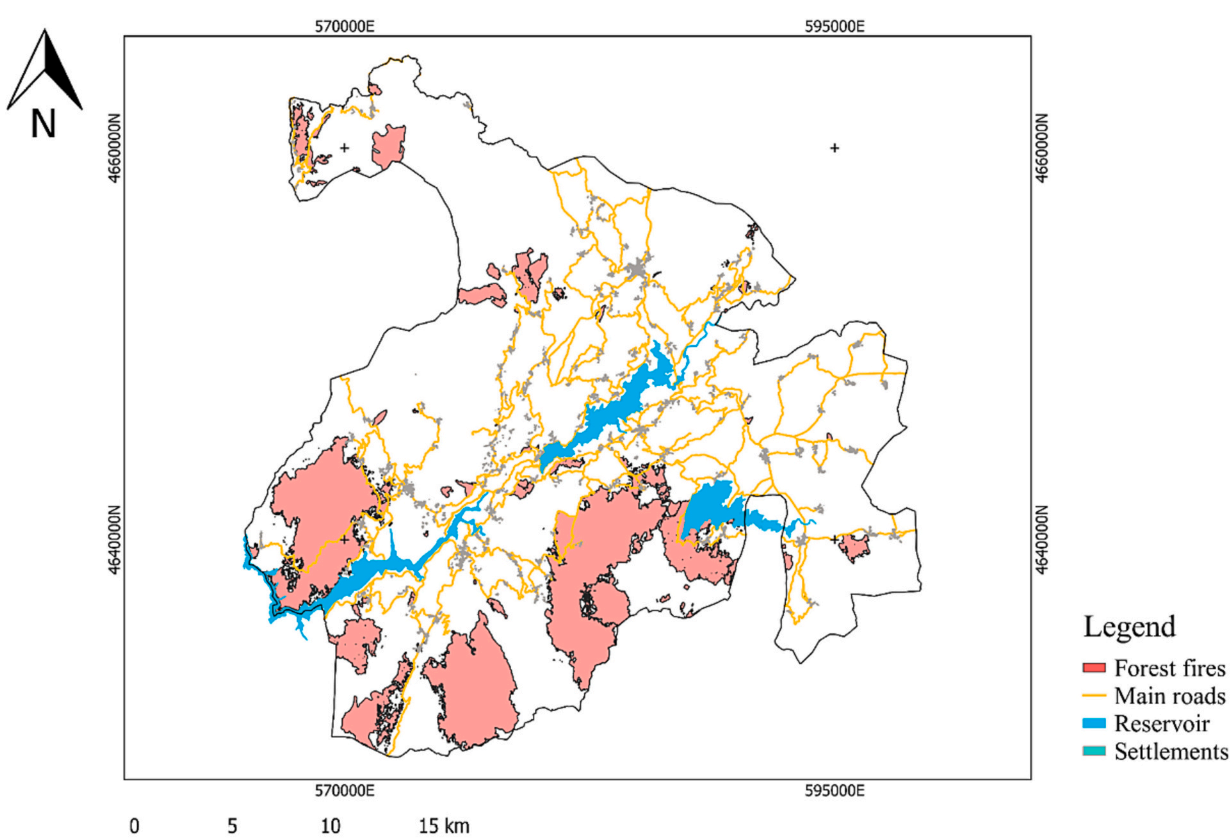

Fig. 3. Forest fires in the study area between 2015 and 2020.

roads and population centres.

For the factors related to the environmental protection plan and land use, a direct link can be seen between the areas protected by the Natura 2000 Network and the largest areas affected (Fig. 5a). The results for the Natura 2000 Network are obtained in line with the degree of protection: 3649.7 ha belong to the protection area and 7076.4 ha to the conservation area. Outside the Natura 2000 Network, there is a further area of 1774 ha affected by fires, i.e. only 14%. According to SIOSE (Fig. 5b), the land uses of the affected areas are as follows: 4896 ha are scrubland, 3735 ha are rocky areas and 2065 ha are forest.

3.3. PLS – PM model

Fig. 6 shows the results for the diagram with a total R^2 of 0.62 for the main endogenous variable on which the paths converge: "Fire factors". This figure is dependent on the direct variables that converge on it. 5 are latent variables and 3 are measured. It also depends on the sample size, which in this case is 56. With this data, for a significance level of 5% the R^2 is above the accepted range, which is 0.25–0.50 for sample sizes between 54 and 84. This is not the case for the latent variable "Environmental factor", which in turn depends on the climate variable. This has a very low R^2 of 0.044.

Eqs. 4–9 show the measured score (MS) for each latent variable and the predicted score (PS) (10,11).

$$MS_{ENVIRONMENTAL} = MAX\_ALTITUDE \cdot 0.481 + MED\_ALTITUDE \cdot (-0.220) + MAX\_SLOPE \cdot 0.757 + MED\_SLOPE \cdot (-0.034) \tag{4}$$

$$\mathrm{MS_{TERRITORIAL}} = \%\_\mathrm{FOREST}\cdot 0.501 + \%\_\mathrm{SCRUB}\cdot 0.803 + \%\_ROCKY\cdot 0.696 \tag{5}$$

$$\mathrm{MS_{ENVIRONMENTAL\_PROTECTION}} = \%\_\mathrm{CONSERV\_AREA}\cdot 0.587 + \%\_\mathrm{PROTEC\_AREA}\cdot 0.591 \tag{6}$$

$$\mathrm{MS_{ANTHROPOGENIC}} = \%\mathrm{ROAD\_} < 100mts\cdot(-0.195) + \%\mathrm{ROAD\_} > 1000mts\cdot 0.428 + \%SETTLEMENT\_ < 500mts\cdot 0.074 + \%SETTLEMENT\_ > 3000mts\cdot 0.866 \tag{7}$$

$$\mathrm{MS_{FIRDEFENSE}} = \%\mathrm{WATERPOINT\_} < 500mts\cdot 0.959 + \%\mathrm{WATERPOINT\_} < 1000mts\cdot 0.450 + \%\mathrm{WATERPOINT\_} < 1500mts\cdot 0.549 + \%\mathrm{WATERPOINT\_} < 2000mts\cdot 0.571 \tag{8}$$

$$\mathrm{MS_{CLIMATIC}} = RH\cdot(-0.98) + \mathrm{PRECIPITATION}\cdot 0.711 + \mathrm{TEMPERATURE}\cdot 0.903 \tag{9}$$

$$\mathrm{PS_{FIREFACTORS}} = \mathrm{MS_{ENVIRONMENTAL}}\cdot 0.384 + \mathrm{MS_{TERRITORIAL}}\cdot 0.101 + \mathrm{MS_{ENVIRONMENTAL\_PROTECTION}}\cdot 0.537 + \mathrm{MS_{ANTHROPOGENIC}}\cdot(-0.136) + \mathrm{MS_{FIRDEFENSE}}\cdot(-0.145) \tag{10}$$

$$\mathrm{PS_{ENVIRONMENTAL}} = \mathrm{MS_{CLIMATIC}}\cdot 0.210 \tag{11}$$

Each latent variable generates a path with an R^2 where the overall

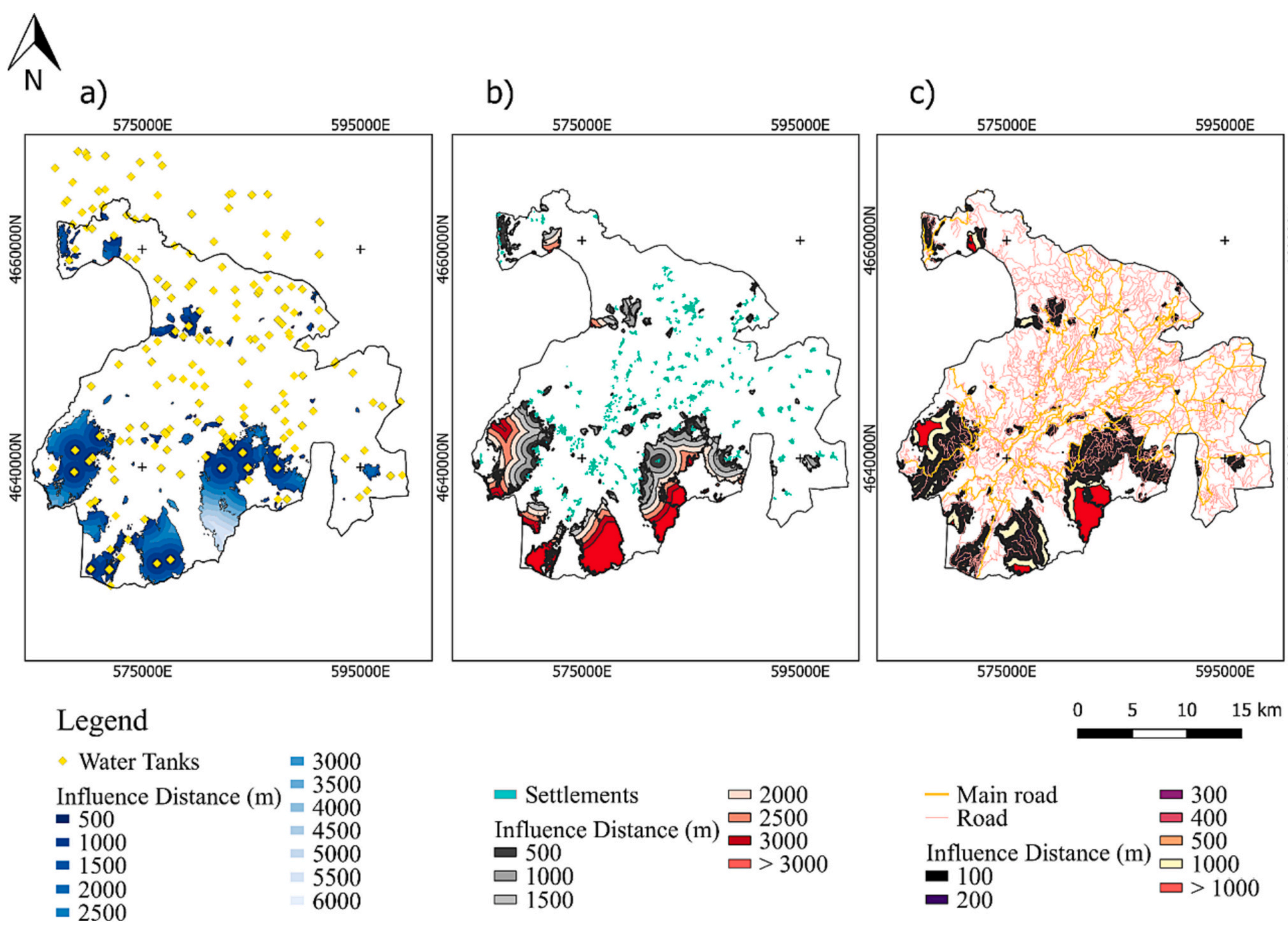

Fig. 4. Anthropogenic factors in the study area. Influence of distance in the different measured variables. Fig. 4a) water points. Fig. 4b) settlements and Fig. 4c) roads.

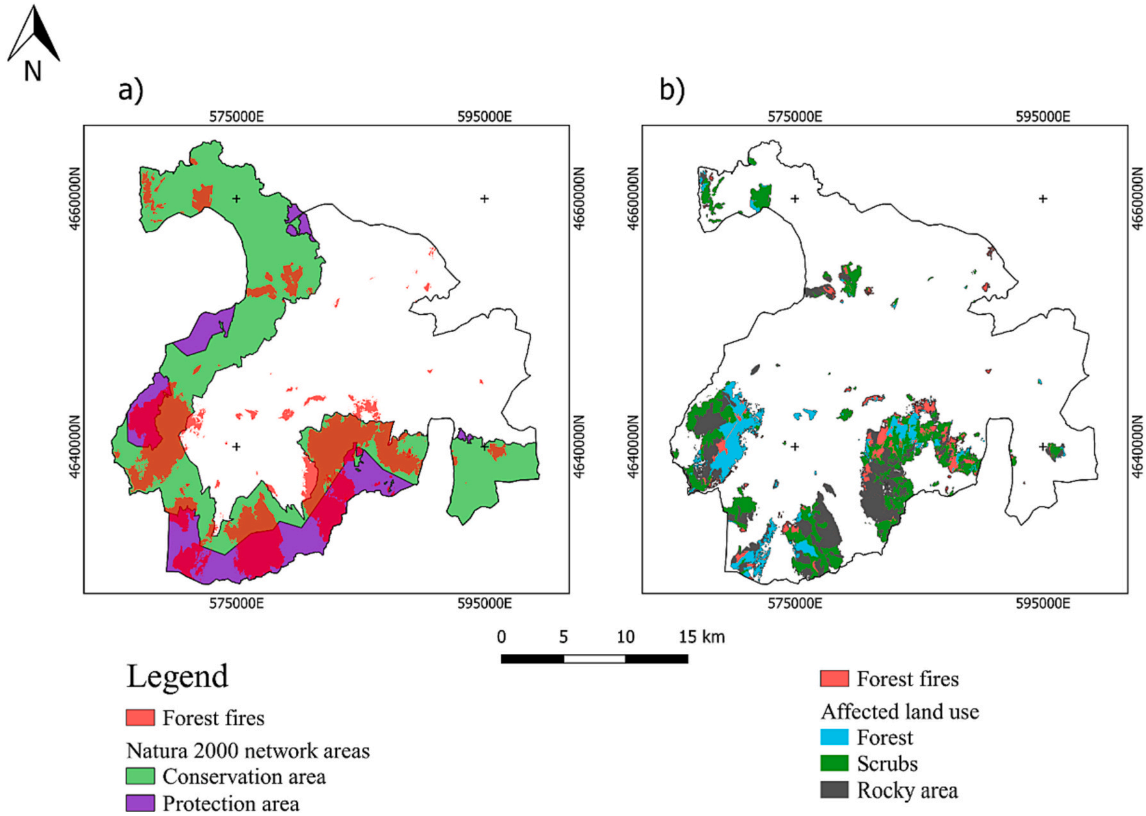

Fig. 5. Environmental and protection management factors in the study area. Fig. 5a) Natura 2000 Network areas affected by fires from 2015 to 2020. Fig. 5b) Land uses affected according to SIOSE.

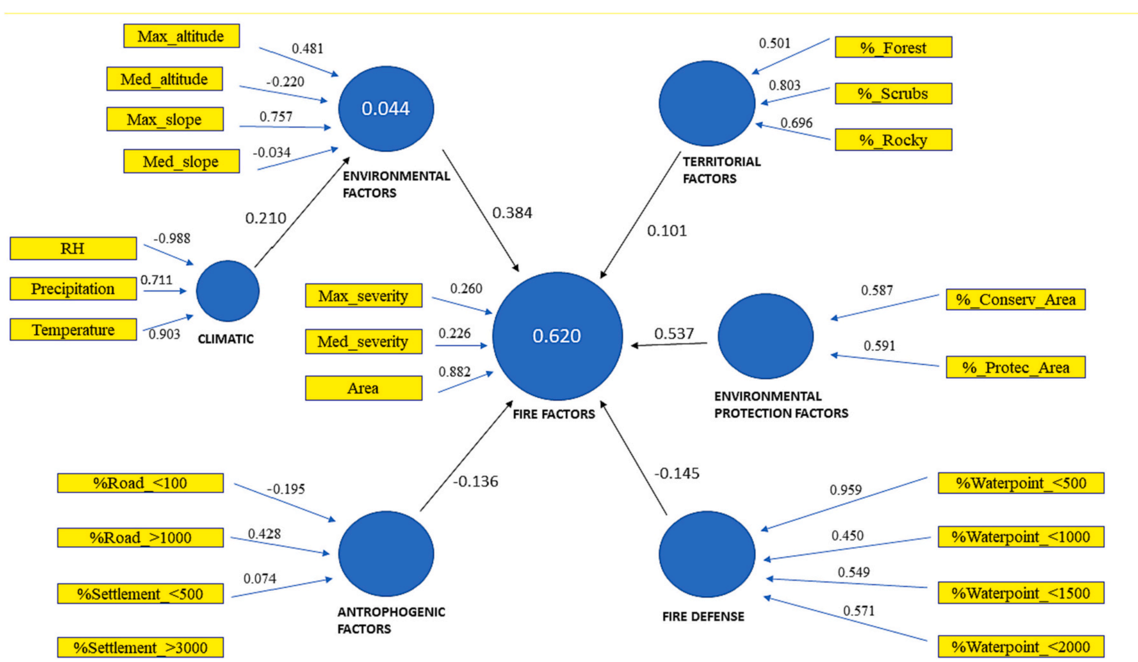

Fig. 6. Coefficients of PLS-PM diagram.

correlation with the main variable can be seen (Table 4). The variable most closely correlated with the spread of fires is "Environmental Protection", with a figure of 0.537. The next most influential variable is "Environmental" (0.384). As can be seen in eq. (1), this is mainly due to the altitude and maximum slopes where fires occur. The variables "Anthropogenic" and "Fire Defense" show a slight negative link (−0.136 and − 0.145 respectively) because their measured distances from roads, towns, and water points help to keep fires away from them. The figure for the variable "Territorial" is the lowest at 0.101. The variable "Climate" has an R^2 of 0.21 for the path to the variable to which it is related, i.e. "Environmental". The external weights of the measured variables (Table 3) show the degree of correlation within each latent variable. For “Environmental” the average altitude and slope variables carry little weight, unlike the maximum values, especially the slope. In “Climate” the three variables measured all have notable effects, with relative humidity being highly negative for the spread of fires and temperature and precipitation being positive. The next most important coefficients are the % of land classed as scrubland (0.803) and rocky ground (0.696) in the “Territorial” variable, the greatest distance from the affected area to a village (%SETTLEMENT_ < 3 km, 0.866) and the closest affected area to water points (%WATERPOINT_ < 500mts, 0.959), in the “Anthropogenic” and “Fire Defense” variables, respectively.

3.4. Sensitivity analysis

The following results are obtained from the sensitivity analysis as detailed in Table 5. The null hypothesis: q = 1 means that we are considering biases that reduce the absolute value of the current estimate. The null hypothesis that is considered problematic is H0:tau = 0. The partial R^2 of the treatment results in 0,13%, so an extreme confusion factor explaining 100% of the residual variance of the outcome must explain at least 0.13% of the treatment variance to exploit the observed estimated effect. With a Robustness value q = 1 the observed factors explaining >3.59% of the residual variance of the treatment and outcome are strong enough to bring the point estimate to 0. Unobserved factors that do not explain >3.59% of the residual variance are not strong enough for a point estimate of 0.

4. Discussion

The initial analysis establishes the degree to which each measured variable is affected by the extent and number of fires. Starting with the direct paths of the latent variables (Fig. 6), “Environmental Protection” has the highest R^2 (0.537). This is because, as can be seen in Fig. 5a, fires occur in these protected areas of the Natura 2000 network. This paradoxical tendency for conservation areas to burn is found where fires are caused by humans, especially in Mediterranean areas (Pereira et al., 2012; San-Miguel-Ayanz et al., 2012). Not only do the vast majority of fires occur in these protected areas, but they also have the largest fires, including all 6 fires of >500 ha.

The second-highest R^2 value is 0.384, for the variable “Environmental”. Many other authors have taken this variable into account when studying forest fires (Barreiro and Hermosilla, 2013; Vega et al., 2009). In this study it contains the parameters related to the terrain (slope and altitude). There is a direct relationship between fires and altitude, but in Spain this variable depends on each region (Ríos-Pena et al., 2017). In the neighboring country of Portugal, which shares the TBR with the study area, there is a stronger relationship between fires and altitude (Catry et al., 2009) far from the coast. However, one would expect that the relationship between this variable and the increase in fires to be higher, since topography, like climate, has played an important role in recent years (Jones et al., 2020; Stevens-Rumann et al., 2018; Vega et al., 2009). The link with the “Environmental” variable is not higher because we decided to include the mean and maximum measurements together in the latent variable. If only the maximum values were included, the result might be more accurate, as they have a greater impact on forest fires. In addition, this study covers a period of 6 years, which is short for studying a fire regime. Finally, one of the variables related to fire spread is fuel, which is measured here by the variable “Territorial”. This takes land use into account. The result shows a low impact (0.101), since the parts of the study area burnt and those that

Table 4
Direct paths of the latent variables.

	Direct Path Coefficients
Anthropogenic Factors	−0,136
Climate - > Environmental	0,21
Environmental Factors	0,384
Environmental Protection Factors	0,537
Fire Defense - > Fire Factors	−0,145
Territorial Factors	0,101

Table 5
Sensitivity Analysis to Unobserved Confounding for the model with outcome the area of fires.

Sensitivity Analysis to Unobserved Confounding					
Treatment:	Coef. estimate	Standard Error	t-value	Partial R^2 treatment with outcome:	Robustness Value q = 1
Temperature	10,0463	47,1765	0,2130	0,0013	0,0359

Table 3
Coefficients of the external weights of the variables measured. Those highlighted in green (positive) and red (negative) have the greatest weight.

	ENVIRONMENTAL	CLIMATE	FIRE	TERRITORIAL	ENVIRONMENTAL PROTECTION	ANTHROPOGENIC	FIRE DEFENSE
MAX_ALTITUDE	0,481						
MED_ALTITUDE	−0,220						
MAX_SLOPE	0,757						
MED_SLOPE	−0,034						
RH		−0,988					
PRECIPITATION		0,711					
TEMPERATURE		0,903					
MAX_SEVERITY			0,26				
MED_SEVERITY			0,226				
AREA			0,882				
%_FOREST				0,501			
%_SCRUB				0,803			
%_ROCKY				0,696			
%_CONSERV_AREA					0,587		
%_PROTECT_AREA					0,591		
%ROAD_ < 100mts						−0,195	
%ROAD_ > 1 km						0,428	
%SETTLEMENT_ < 500mts						0,074	
%SETTLEMENT_ > 3 km						0,866	
%WATERPOINT_ < 500mts							0,959
%WATERPOINT_ < 1 km							0,450
%WATERPOINT_ < 1,5 km							0,549
%WATERPOINT_ < 2 km							0,571

have share the same land characteristics, i.e. they are mainly scrubland. Scrubland and pasture are often associated with wildfires in the north of Spain (Marino et al., 2014). One possible way of mitigating their effects is to work on scrub areas where forest fires are recurrent. Strategically placed strips of trees, or agroforestry zones (already provided in (Xunta de Galicia, 2021a, 2021b)) to break up the brushland can reduce the size and intensity of forest fires. The "Climate" variable has an R^2 of 0.210 in "Environmental", indicating positive climate values of precipitation, temperature, and relative humidity on the ground. High rainfall and humidity mean that during the spring and autumn months scrub and grasses regenerate more quickly. Coupled with high summer temperatures, this results in a large amount of fuel available to burn in short periods each year. Other studies point to a direct link between these climate variables and forest fires in the same region (Galicia)(Chas-Amil et al., 2015; Lombao et al., 2015).

Negative R^2 values on the direct paths of the latent variables are found in "Anthropogenic"(−0.136) and "Fire Defense" (−0.145). The weights assigned do not indicate great importance, but the negative figures demonstrate their contribution to reducing the number and size of fires is proven. For larger study areas, higher densities of roads and population are associated with more human activity, which may lead to an increase in the number of human-caused fires (Calef et al., 2008; Narayanaraj and Wimberly, 2011; Narayanaraj and Wimberly, 2012) In this study, settlements and roads are further away from the fires, as are the water points for extinguishing them, with areas of human activity being prioritized (Oliveira et al., 2020). In this way, points that break up the horizontal continuity of large masses susceptible to fire would be very effective in reducing the extent of fires. Water reservoirs should be located mainly in these areas, far from villages, but difficulties of access and terrain prevent an optimal network of points from being set up.

Analyzing each measured variable and its external weights (Table 3) within the "Environmental" variable, the mean altitude and slope values are found to have no significant weight, while the maximum values are positive and have a high impact (0.481 for altitude and 0.757 for slope). This gives an idea of the importance of slopes in the fires in this study area in the mountains. For the land uses considered, as mentioned above, forest, scrubland, and rocky areas are all present throughout the study area, but an analysis reveals that scrubland has a greater weight, followed by rocky areas and finally the forest species burnt. Although scrubland and rocky areas account for a total of 44% of the land use in the study area, they are mostly found in the unproductive areas bordering Portugal, specially rocks. This is where most of the fires occur, far from the rural centres. In rocky areas, what burns are still scrub species interspersed with granitic formations, which makes it difficult to extinguish the fires. On the other hand, the forest species burned are smaller, since there are no large areas of reforestation. Therefore, the question arises as to whether reforestation is not carried out due to the high frequency of fires, or whether fires occur due to the lack of trees. In regard to the Natura 2000 network, the conservation area and the protection area have very similar R^2 values (0.587 and 0.591). In quantitative terms, the surface area burnt is greater in the conservation area, because it is a larger area per se. The proportion of the smaller protection area burnt (Fig. 5a) is very high, which is a cause for concern.

For the variables measured by distance to roads, the figures for burnt areas within 100 m of a road is slightly negative (−0.195), while that for distances of >1 km is positive (0.428). From this it can be concluded that roads negatively affect fires. Similar results are obtained for the village distance variables. This seems logical in both cases, since large areas of land susceptible to fire do not have the anthropogenic factor nearby. In the case of "Fire Defense", the figure of 0.959 for the area burnt within 500 m of a water point is the highest obtained in the PLS-PM analysis. This can be explained by the fact that the areas likely to burn do contain at least some water (Fig. 4a). As distances increase to 2 km, the figures all remain constant at around 0.5, so it cannot be concluded that the greater the distance, the greater the fire spread due to the influence of the point network. One of the anthropogenic factors that may be directly related to the increase in forest fires is the abandonment of agricultural land in the study area. In this sense, the ageing of the population, together with depopulation, are of particular importance in the area. Livestock farms, which are essential for maintaining low fuel load levels, have also been strongly reduced, from 600 to just over 100 in the last 20 years (IGE, 2021). Moreover, specifically in the case of the Xures Natural Park, there is no master plan for use and management from 1998 to 2021. This makes the situation more difficult for a better management of socio-economic activities and lines of action, especially needed in environmentally protected areas, which are likely to accumulate more fuel load. Finally, and in relation to the distances to urban centres, roads and forest tracks, the 2007 Galician fire law specifies the distance and maintenance of the biomass strips, in terms of fire prevention (Xunta de Galicia, 2007). All the assumptions are included in the law, but compliance sometimes does not come in time, due to the large number of owners responsible for the maintenance of the biomass strips. This is one of the main problems of rural Galicia, where there are about 11.1 million rustic cadastral plots belonging to 1.73 million owners which is a problem in the efficient management of administrative procedures in relation to these plots and the owner (Consellería del Medio Rural, 2022).

The choice of the variable highlighted for model analysis through parameter sensitivity (temperature in this case) is made because it is the most important characteristic in the fire problem, thus explaining more of the residual variation than other unobserved confounding factors. The fire period where the largest fires occur (May to October) influences the weight of the climatic variables, as well as the precipitation variable, although other variables such as fuel patterns may have more weight and be analyzed in more depth.

5. Conclusion

The remote sensing techniques used have enabled us to map the burnt areas in the Transboundary Biosphere Reserve in this part of Spain in 2015–2020. In total, 12,500 ha of land has burned in 56 fires. PLS-PM analysis has been used to determine what variables have the greatest weight in the problem of these forest fires. The absence of the human factor and more steeply sloping terrain are found to contribute directly to a greater number and size of forest fires in the study area. This, in turn, coincides with the areas with some type of environmental protection, which shows that the problem calls for changes in fire prevention and rural development policies. One effective measure is the creation of breaks in the horizontal continuity of fuel through strategic points in large fire-prone areas. GIS tools and the numerous databases available quickly and clearly show the areas of action and decision-making of the competent authorities. For future studies, it is recommended that the study period of the fires be extended and that socio-economic variables be included as well as more precise data on the number of fires and ignitions. This can be compared with different protected areas of high biodiversity in Spain with similar characteristics.

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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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