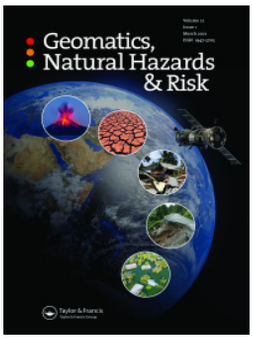

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RESEARCH ARTICLE

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Assessing environmental and anthropogenic drivers for the occurrence and extent of fires in high Andean Grasslands

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ABSTRACT

The grasslands of the southern Andes are critical ecosystems for the rural population, but they have been significantly affected by fires. While fire ignitions are anthropogenic, their occurrence and spread are shaped by climatic, vegetational, and topographic factors. This study identified the main environmental and human drivers of fire occurrence and extent in high Andean grasslands. We developed generalized linear models with 14 and 22 variables for the fire occurrence and extent model, respectively. Various metrics (e.g. AIC, AUC, pseudo-R^2) were applied to validate the best-performing model and assess its performance. Our findings suggest that elevation, maximum temperature, soil adjusted vegetation index, and topographic position index are the primary drivers of fire occurrence. For fire extent, grass cover, elevation, topographic position index, and rock cover were the most influential factors. The models explained 21% and 60% of the variability in fire occurrence and extent, respectively. This study identifies key environmental factors influencing fire occurrence and extent, providing valuable insights for improving fire management strategies, particularly in fire-prone ecosystems such as grasslands. Since the temperature was a contributing factor to fire occurrence, this highlights the importance of prevention and reduction strategies in the context of climate change.

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Grassland fires; fire occurrence; fire extent; SAVI; environmental and anthropogenic factors

Introduction

Fire is an increasingly influential disturbance that shapes the structure and functioning of diverse ecosystems (Abram 2021; Zubieta 2023b). Its regime, characterised by size, intensity, frequency, seasonality, and patchiness, has changed over time (Keeley and Pausas 2022; Pausas 2022). Some ecosystems have evolved with naturally occurring fires (fire-dependent) (Murphy et al. 2008; Pausas and Lamont 2022), while others have not evolved under such disturbances (fire-independent) (Cardille et al. 2001), leading to various ecological consequences. Fire not only alters species structure and composition (Overbeck et al. 2018; Hernández 2021; Rainsford et al. 2022) and ecosystem functions (Bengtsson 2019; Bowman et al. 2020), but also generates negative economic and social impacts (Leverkus et al. 2020; Abram 2021). In countries where fires are part of the evolutionary history of their ecosystems, there is a deep understanding of their causes and effects. This knowledge has led to the development of strategies such as live fences and prescribed burning to mitigate and control their impacts (Bowman et al. 2020; Hopkinson et al. 2020).

In South American countries, knowledge about fires remains limited (Armenteras et al. 2020). Gaining a better understanding of their causes and impacts is a priority, particularly as fire frequency increases and poses a growing threat to high Andean grasslands (Armenteras et al. 2020; Zubieta 2023b). These fires, which are primarily of anthropogenic origin (Kirkpatrick et al. 2011; Oliver et al. 2017), can be intentional,

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as part of pasture management for livestock (Armenteras et al. 2020), or unintentional, resulting from crop residue burning or land clearing (Alvarez et al. 2024; Luna-Celino and Kainer 2024). In this ecosystem, natural fires are extremely rare because biomass production is around 6.7 Mg/ha (Oliveras 2014b), which is considerably lower than in temperate ecosystems where natural fires are common and fuel consumption ranges from 34 to 88 Mg/ha (Stocks and Kauffman 1997). In Peru, most fires occur in rural areas at altitudes between 3500 and 4500 m (Zubieta 2021), where limited access and long distances hinder timely control efforts. Consequently, the Peruvian National Institute of Civil Defence (INDECI) reports only approximately 4% of fires as emergencies (Zubieta 2023b), with distance to access roads being a key factor in fire occurrence (Mahdavi et al. 2012; Abdi et al. 2018). Although ignition sources are anthropogenic, environmental factors also play a significant role in the occurrence and extent of grassland fires.

The environmental factors influencing the occurrence and extent of fires have been studied in various geographical areas (e.g. Australia, Africa, North America), primarily in forests. However, research on grasslands, particularly in Peru, remains limited (Armenteras et al. 2020), underscoring the need to consider the influence of local factors (Zubieta 2021; de Oliveira 2023; Zubieta 2023b). Climatic factors, such as the accumulated frequency of dry and hot days, are directly linked to increased fire occurrence (Zubieta 2021), especially in areas where cattle ranching is restricted (Aráoz and Grau 2010; Kirkpatrick et al. 2011; Montti et al. 2021). Similarly, higher temperatures are associated with greater fire occurrence (Mahdavi et al. 2012; Buthelezi et al. 2016; Mpakairi et al. 2019). Additionally, elevation (Mahdavi et al. 2012), slope (Yang et al. 2007; Abdi et al. 2018), and other parameters derived from digital elevation models, such as the topographic position index (Harris and Taylor 2017), have been shown to influence fire occurrence and severity. These climatic and topographic factors, which vary at large to medium spatial scales, interact with more local factors.

Local factors, such as biomass availability (Cruz et al. 2018) and plant community composition (Mpakairi et al. 2019; Parker et al. 2022), influence fire occurrence and extent. Rather than a lack of dry biomass, the amount of fuel limits fire occurrence (Carilla and Grau 2010). Therefore, evaluating the response of grasslands to fire in arid regions requires considering the dominant species and their structure (Killgore et al. 2009). For instance, communities dominated by fine elements (grasses, branches with diameters < 6 mm) (Dewar 2021; Parker et al. 2022) and scleromorphic elements (Kirkpatrick et al. 2011) are associated with higher fire occurrence and spread (Wragg et al. 2018; Sühs et al. 2020). In communities where scleromorphic elements and non-palatable grasses dominate, livestock has a reduced impact on fuel availability (Kirkpatrick et al. 2011), increasing the likelihood of fire occurrence.

Identifying the environmental and anthropogenic factors that influence fire occurrence and extent is crucial in a country where grasslands provide multiple ecosystem services (Bengtsson 2019), including erosion prevention, climate regulation, biomass for livestock production, and cropland production. Additionally, Peru is among the countries most affected by climate change (Wongchuig et al. 2018), which could further exacerbate the occurrence, frequency, and spread of fires due to more frequent temperature and precipitation anomalies (Achard et al. 2008; Abram 2021). This increased occurrence of fires would result in human and material losses, in addition to impacts on wildlife, as occurred in 2022 when vicuña populations were affected. This study prioritises identifying the factors that contribute to fire occurrence and extent in the high Andean grasslands of southern Peru. Therefore, the research objectives were: (1) to identify the environmental and anthropogenic factors that determine fire occurrence and (2) to identify the environmental, anthropogenic, and vegetation factors that determine the extent of grassland fires. The information obtained by addressing these questions can support stakeholders involved in fire management. Furthermore, despite the ecological importance of high Andean grasslands, the combined influence of environmental and anthropogenic drivers on fire occurrence and extent in Peru remains poorly understood.

Materials and methods

Study area

The study area is located in southern Peru, within the provinces of Melgar, Azángaro, and Lampa in the Puno region (Figure 1). These provinces experience the highest fire frequency during the dry season

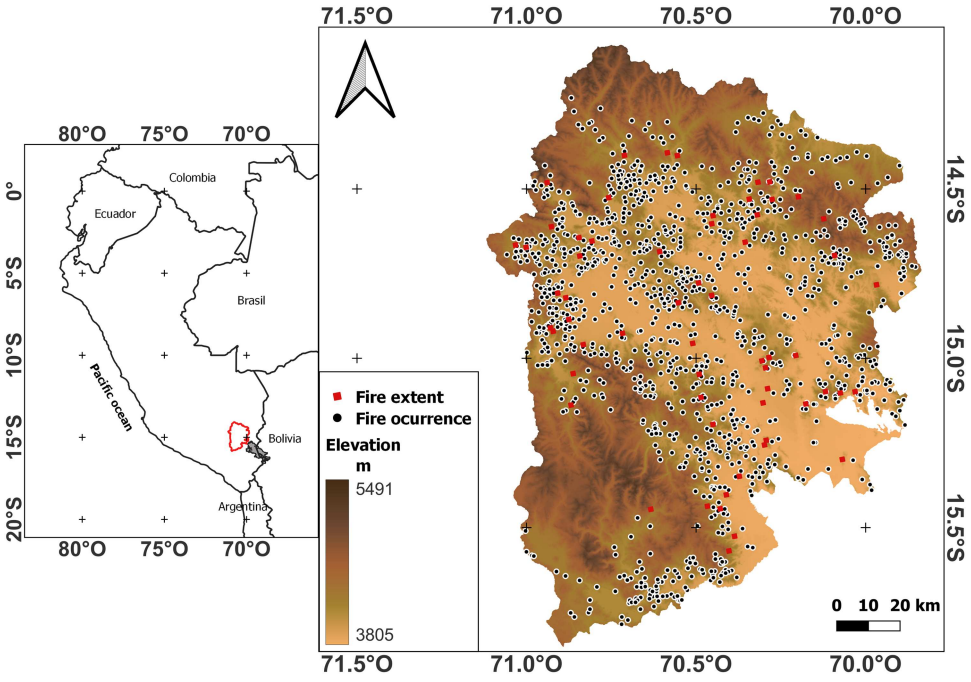

Figure 1. Location of the study area showing the elevation gradient. Black circles represent fires that occurred between 2017 and 2023, used to model fire occurrence ($n = 1265$), while red diamonds indicate the centroids of fire scars assessed for modelling fire extent ($n = 60$).

(Zubieta 2023b). The climate is characterised by annual precipitation ranging from 441 to 837 mm, with a substantial reduction in winter (11–19 mm). Temperatures range from—5.9 to 16.3 °C, with the lowest values recorded in winter and the highest during the winter-to-spring transition (Imfeld 2021). The study area belongs to the montane scrub and grassland biome (Olson 2001), characterised by the presence of highly combustible elements, including species from the *Festuca*, *Jarava*, *Stipa*, *Calamagrostis*, *Poa*, and *Bromus* genera, as well as sclerophyllous elements, including species from the *Baccharis*, *Parastrephia*, *Tetraglochin*, and *Chersodoma* genera.

Response variable acquisition

Fire occurrence points were obtained from the National Forestry and Wildlife Service, which manages historical records of fire occurrences nationwide. We analysed data from fires that occurred between 2017 and 2023. After removing duplicate points and enforcing a minimum distance of 500 m between points, we obtained 1265 occurrence points. Using QGIS (v 3.22.10) (QGIS Development Team 2022), we generated 5000 random absence points (pseudo-absences) (Stockwell and Peters 1999), excluding those located over water bodies or urban areas (Lobo et al. 2010). A minimum distance of 500 m was also maintained between these points, resulting in 4027 pseudo-absence points. This distance was adopted following Alfaro (2021) and to ensure one point per pixel, given that the spatial resolution of the raster products was 0.5 km. To address classification bias—often caused by classifiers being more sensitive to detecting the majority class (pseudo-absences) over the minority class (fire occurrence)—the dataset was balanced to 1265 points for each class.

We used Sentinel 2 satellite images at processing level 2 A, acquired from the European Space Agency https://dataspace.copernicus.eu), to delineate the extent of the 23 and 37 fires assessed in 2023 and 2024, respectively. The mean of the evaluated fire scar extent was 155.06 ± 29.92 ha. The downloaded images correspond to the following tiles: T19LBE, T19LBD, T19LBC, T19LCE, T19LCD, T19LCC, and T19LDD. For image classification, the following classes were considered: burned areas, bare soil (wasteland, fallow, and ploughed land), water bodies (rivers and lakes), vegetation (crops/pastures, grasslands, wetlands,

hydrophilic vegetation, and forests), urban areas, shadows, and clouds. Image classification was performed using the Random Forest method (Cutler 2007) and validated using Cohen's Kappa index, with results considered valid when the index exceeded 0.8 (Sühs et al. 2020). Classification and validation were conducted in R (v 4.1.3) (R Core Team 2022), where the Kappa index ranged from 0.94 to 0.98. Additionally, manual correction of burned areas was applied in all cases.

Independent variable acquisition

Climatic variables

Climatic variables were obtained from the PISCO database (Peruvian Interpolated data of SENAMHI's Climatological and Hydrological Observations). From this dataset, we generated the accumulated frequency of hot days (HDF) (2005–2016) and the accumulated frequency of dry days (DDF) (2005–2020) from May to November, following the methodology of Zubieta (2021). Similarly, maximum temperature (MaxT) and potential evapotranspiration (PE), calculated from May to November, were used for the period 2005–2016. We considered these variables because various studies have identified them as the most influential in fire occurrence and because they are directly related to vegetation flammability. All variables were rescaled to a spatial resolution of 0.5 km using the Kriging interpolation method in R (v 4.1.3) (R Core Team 2022).

Topographic variables

Topographic variables were derived from 30 m spatial resolution Digital Elevation Models (DEMs), obtained from the ASTER Global DEM satellite, part of the Terra ASTER collection of Japan Space Systems. The generated variables included slope, aspect, elevation, Topographic Wetness Index (TWI), and Topographic Position Index (TPI). Exposure was classified into four categories based on the level of solar radiation received (Table 1). The TPI was calculated using pixels within a 500, 1000, and 2000 m radius, following the method of De Reu (2013) in R (v 4.1.3) (R Core Team 2022). The TWI was generated in SAGA GIS (v 7.8.2) (Mattivi et al. 2019), while the other variables were produced in QGIS (v 3.22.10) (QGIS Development Team 2022). All variables were rescaled to a spatial resolution of 0.5 km using the bilinear method in R (v 4.1.3) (R Core Team 2022).

Anthropogenic variables

Anthropogenic variables analysed included the distance to roads, the distance to residential areas, and grazing intensity. Geospatial data for roads and residential areas were obtained from the Ministry of Transport and Communications and the Ministry of Education of Peru, respectively. This information was rasterised, and the Euclidean distance was calculated using QGIS (v 3.22.10) (QGIS Development Team 2022), at a spatial resolution of 0.5 km. To determine grazing intensity, eight transects, each 50 metres long, were established around each fire scar. Two transects were established in each cardinal direction, located on the right and left sides of the plots used to assess vegetation structure (described below). Within each transect, 25 quadrats of 1 m^2, spaced 1 m apart, were set up to record the presence or absence of cattle faeces. A faecal abundance index was calculated as the frequency of quadrats with faeces presence (Carilla and Grau 2010). The average value across the eight transects was used for subsequent analysis.

Table 1. Description of aspect classification.

Aspect	Grades	Class
Sunny slope	0—67.5, 337.5—360	1
Semi sunny slope	67.5—112.5, 292.5—337.5	2
Shady slope	157.5—247.5	3
Semi shady slope	112.5—157.5, 247.5—292.5	4

Vegetation variables

The Soil Adjusted Vegetation Index (SAVI) was calculated using images from the MODIS sensor aboard the Terra satellite, specifically the MOD09A1 product (collection 06), with a spatial resolution of 0.5 km and a temporal resolution of 8 days (Vermote 2021). The index was determined for the period from May to November, between 2017 and 2023. SAVI was selected due to its suitability for studying arid areas with sparse vegetation and exposed soil surfaces (Huete 1988). Additionally, it serves as an indicator of vegetation biomass and has been widely used in studies related to mapping, modelling, fuel load estimation, and fire risk assessment (e.g. Arnett et al. 2015; Bao et al. 2022). Before calculating SAVI, the near-infra-red and red bands underwent atmospheric correction to minimise the effects of energy scattering caused by gas and aerosol concentrations. For this purpose, we used the quality band (sur_refl_state) provided by the MOD09A1 product.

To assess the effect of vegetation structure on fire extent, four 30 × 30 m plots were established around each fire scar (Delcourt 2021; van Gerrevink and Veraverbeke 2021). A total of 60 fire scars were evaluated between 2023 and 2024. The plots were located in homogeneous areas, oriented toward the four cardinal directions, and positioned at least 30 m from the burned area. Additionally, they were situated more than 50 m away from any road. The sampling points were initially identified using satellite images and later validated in the field. Geographic coordinates were recorded at the centre of each plot. Along the perimeter of each plot, vegetation height and cover type were recorded every 1 m using the intercept point method. Cover types included grasses, woody herbs, bare soil, rock, and leaf litter (Drezner and Drezner 2021). The percentage of each cover type was calculated from these records. The average values from the four plots were used for subsequent analyses. Also, five 0.5 × 0.5 m quadrats were placed at the four corners and the centre of each plot to collect aerial biomass samples. Samples were stored in labelled paper bags, then cleaned and oven-dried at 90 °C for 24–48 hours until reaching a constant weight for dry mass determination. The analyses were performed using the average values from the five quadrats and the four plots.

Data pre-processing

For the occurrence model, presence and pseudo-absence data were overlaid on all stacked raster variables to extract variable values. In the extent model, raster variable values were extracted from the polygons of each fire. To mitigate the effects of differences in dimension and magnitude, all variables—except aspect and SAVI—were normalised (Table 2).

The occurrence model included 14 variables, whereas the extent model considered 22 variables (Table 3).

Modelling and evaluation of the fire occurrence and extent model

We used Generalised Linear Model (GLM) to model fire occurrence and extent (Cardille et al. 2001; Marques 2011). The occurrence dataset was split into training (80%) and validation (20%) subsets. Fire occurrence was modelled using GLMs with the binomial family and a logit link function. Fire extent was modelled using GLMs with a negative binomial family and a log link function, utilising the entire database due to the small sample size. The values used for the fire extent model were the mean of all pixel values extracted from each polygon corresponding to each fire scar.

Table 2. Normalisation formulas.

Formula	Description	Variables using the transformation
$x_i^* = \frac{x_i - x_{min}}{x_{max} - x_{min}}$	x_i and x_i^*, variable values before and after the normalisation, respectively. x_{max} and x_{min}, correspond to the maximum and minimum value of the entire dataset for each variable, respectively.	HDF, DDF, MaxT, TPI, TWI, PE, elevation, distance from fire to road, distance from fire to residential area, dry mass, and all types of cover.
$x_\alpha = \sin \alpha$	α, slope value	Slope

Table 3. Environmental and anthropogenic variables used in modelling the occurrence and extent of grassland fires. The superscript numbers indicate whether the variable was used in the occurrence model ([1]) or the fire extent model ([2]).

Response variable	Factor	Variable
Fire occurrence (1), fire extent (2)	Climate	[1,2]HDF (accumulated frequency of days with a temperature higher than 20 °C)
		[1,2]DDF (accumulated frequency of days with rainfall lower than 1 mm)
		[1,2]MaxT (°C)
		[1,2]PE (mm/month)
	Topography	[1,2]Slope (grades)
		[1,2]Aspect (class)
		[1,2]Elevation (m)
		[1,2]TWI
		[1,2]TPI 500, 1000 and 2000 m
	Vegetation	[1,2]SAVI
		[2]Grass cover (%)
		[2]Herbs cover (%)
		[2]Woody species cover (%)
		[2]Bare soil cover (%)
		[2]Rock cover (%)
		[2]Litter cover (%)
		[2]Dry mass (g)
	Anthropogenic	[1,2]Distance from fire to road (m)
		[1,2]Distance from fire to residential area (m)
		[2]Grazing intensity (%)

Table 4. Evaluation results of the five best GLMs for fire occurrence. Values represent the mean across five cross-validation iterations using the testing dataset. The best-performing model is highlighted in bold.

Code	SE	Precision	F1-score	SP	Accuracy	AUC	GG
b.glm.m5	**0.826**	**0.700**	**0.757**	**0.645**	**0.736**	**0.790**	**−0.003**
b.glm.m88	0.840	0.700	0.763	0.632	0.738	0.786	0.005
b.glm.m89	0.839	0.690	0.757	0.613	0.728	0.778	0.016
b.glm.m91	0.833	0.684	0.750	0.616	0.724	0.775	0.017
b.glm.m92	0.828	0.711	0.765	0.645	0.740	0.793	−0.005

SE: Sensitivity, SP: Specificity, GG: generalisation gap.

For both the occurrence and extent models, variable selection was based on evaluating all possible combinations of explanatory variables exhibiting a correlation coefficient greater than 0.1 with the response variable. This threshold was chosen because most explanatory variables had a correlation below 0.6 with the response variables (Appendix 1 and 2). Additionally, only explanatory variables with correlations below 0.5 between them were retained for model construction. To prevent multicollinearity, we applied the Variance Inflation Factor (VIF) and Generalised Variance Inflation Factor (GVIF) tests, ensuring that values remained below five (Fox and Monette 1992).

The best model was selected based on Akaike's Information Criterion (AIC) for fire occurrence and the corrected Akaike's Information Criterion (AICc) for fire extent (Akaike 1974), along with McFadden's adjusted pseudo-R^2 (Guisan and Zimmermann 2000) and GVIF. The significance of model variables was assessed using the Wald test. To validate the fire occurrence model, a confusion matrix of validation data (Appendix 3) was used to calculate sensitivity, precision, F1-score, specificity, accuracy, area under the receiver operating characteristic (AUC), and AUC generalisation gap. All statistical analyses were conducted in R (v 4.1.3) (R Core Team 2022).

Results

Fire occurrence

Among the 15 best models generated (Appendix 4 and 5), five demonstrated high performance in modelling fire occurrence. Of these, the b.glm.m5 model was the most parsimonious based on the selected performance metrics.

The b.glm.m5 model achieved an accuracy of 73.6%, with precision and sensitivity of 70% and 82.6%, respectively. The F1-score (75.75%) indicated a well-balanced performance, combining high sensitivity and accuracy. The average AUC generalisation gap was—0.003, indicating no overfitting and confirming the model's robustness with the validation data (Table 4).

The b.glm.m5 model exhibited significant coefficients for nearly all variables, demonstrated low multicollinearity, and achieved the highest AUC (0.790) (Table 4).

The b.glm.m5 model accounted for 20.2% of the variation in fire occurrence, with elevation, maximum temperature, SAVI, and TPI 1000 m identified as key determining variables. Based on absolute *Z*-statistic values, the quadratic term of elevation ranked as the most important factor, while the quadratic term of SAVI ranked the least (Table 5).

The effect of all explanatory variables in the selected model, based on their sequential contribution to reducing the residual deviation of fire occurrence, was significant ($p < 0.001$) (Table 6). These results aligned with the overall significance order determined by the Wald test (Table 7).

Among the explanatory variables, elevation was the most influential, contributing 60.12%, followed by maximum temperature (21.87%), SAVI (11.13%), and TPI 1000 m (6.88%) (Table 7).

The probability of fire occurrence increased with elevation up to 4220 m before declining (Figure 2a). A similar trend was observed for maximum temperature, with fire probability peaking at 17.26 °C before decreasing (Figure 2b). Likewise, SAVI showed the highest probability of fire occurrence at an index of 0.15 before declining (Figure 2c). In contrast, fire probability increased steadily with TPI 1000 m (Figure 2d).

The model's AUC value of 0.790 indicates strong predictive performance, surpassing a random classifier (Figure 3).

Fire extent

Among the ten best models generated (Appendix 6 and 7), five demonstrated strong performance in modelling grassland fire extent. The bn.glm.m7 model met all the selection criteria and identified four key variables influencing fire extent (Table 8).

The bn.glm.m7 model featured significant coefficients for nearly all linear and quadratic variables, exhibited low multicollinearity, and had one of the lowest AICc values (Table 8).

Table 5. Summary of the best GLM (b.glm.m5) for modelling fire occurrence, including estimated coefficients and significance levels for explanatory variables (linear or quadratic terms). Model performance metrics: AIC = 2249.84, adjusted pseudo-R^2 = 0.202.

Variables	Estimated coefficient	Standard error	*Z*-value	*p*-value
(Intercept)	−0.174	0.051	−3.432	<0.001
MaxT, 1	26.950	3.394	7.940	<0.001
MaxT, 2	−23.556	3.455	−6.819	<0.001
Elevation, 1	−32.454	3.923	−8.272	<0.001
Elevation, 2	−54.214	3.519	−15.408	<0.001
TPI1000, 1	15.520	2.733	5.678	<0.001
TPI1000, 2	1.088	2.726	0.399	0.690
SAVI, 1	−22.187	3.009	−7.374	<0.001
SAVI, 2	1.085	3.418	0.317	0.751

Table 6. Wald test results for the explanatory variables in the selected model (b.glm.m5).

Variables	df residuals	Residual deviance	df	Wald test	*p*-value
MaxT	2527	3314.74	2	69.727	<0.001
Elevation	2525	2903.62	2	186.808	<0.001
TPI 1000	2523	2850.02	2	26.161	<0.001
SAVI	2521	2791.14	2	48.560	<0.001

Table 7. Ranking of explanatory variables in the selected GLM based on General Dominance Analysis using the full dataset for modelling fire occurrence. Values represent the average conditional contribution of each variable to the pseudo-R^2 across all possible subset models.

Variable	Importance order	Average contribution to pseudo-R^2	Scaled values	Relative contribution
Elevation	1	0.128	100.000	0.601
MaxT	2	0.045	28.165	0.219
SAVI	3	0.023	7.998	0.111
TPI1000	4	0.014	0.000	0.069

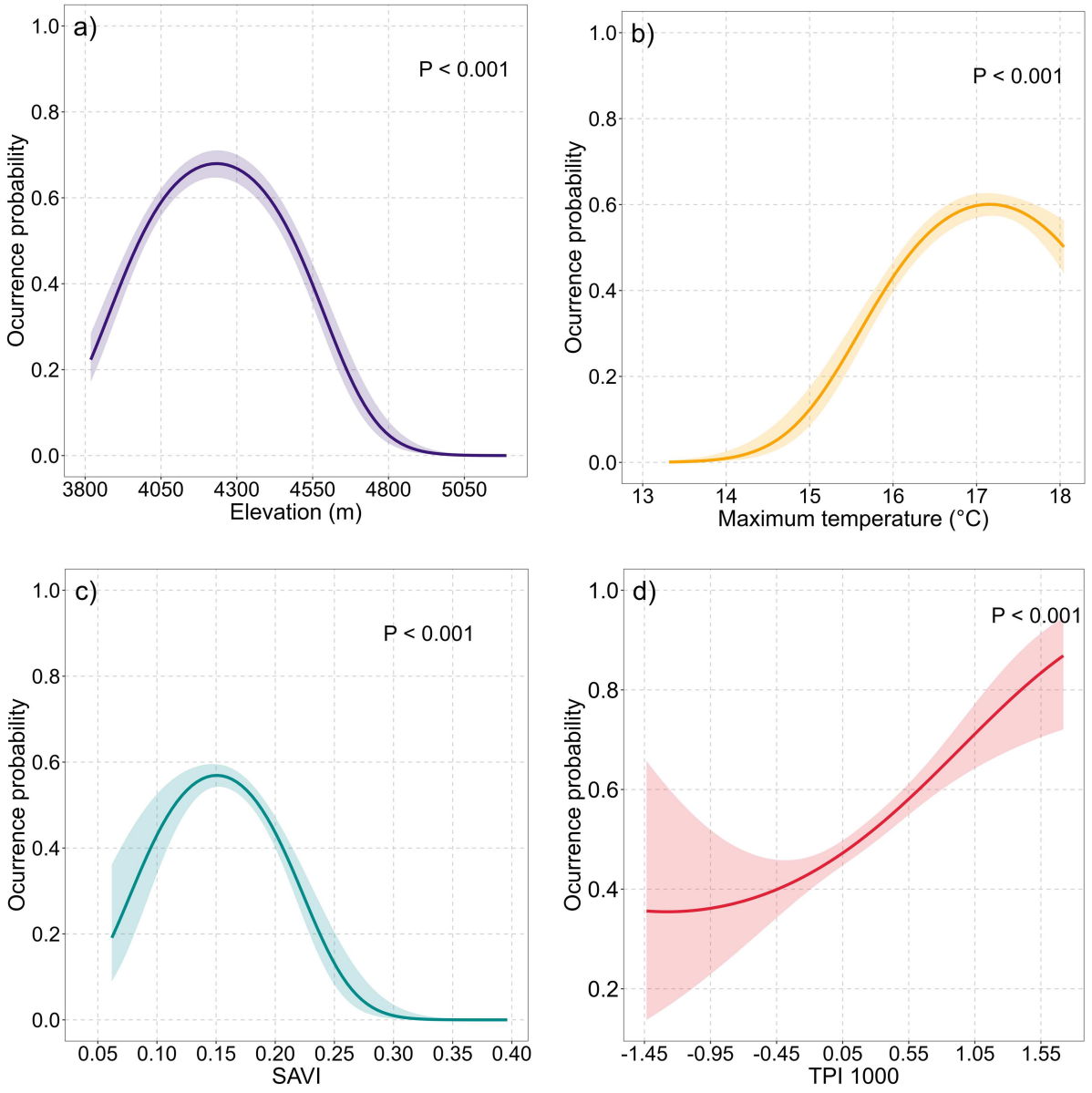

Figure 2. Relationship between elevation (a), maximum temperature (b), SAVI (c), and TPI 1000 m (d) with fire occurrence based on the best GLM (b.glm.m5). The lines depict the variations in fire probability as explanatory variables change, while the shaded areas represent the 95% confidence interval.

The bn.glm.m7 model explained 60.1% of the variation in fire extent. Based on the absolute values of the *Z*-statistic, the quadratic term for rock cover was the most influential variable, while the quadratic term for elevation had the least impact (Table 9).

The explanatory variables in the selected model significantly contributed to reducing residual deviance in fire extent (Table 10), aligning with the overall importance ranking (Figure 4).

The importance ranking of the explanatory variables in the selected model identified grass cover as the most influential factor (45.90% contribution), followed by TPI 2000 m (32.70%), elevation (13.89%), and rock cover (7.51%) (Figure 4).

Grass cover had a positive linear effect on fire extent (Figure 5a). Fire extent peaked at TPI 2000 m values between 3.24 and 3.26 (Figure 5b). Similarly, fire extent increased with elevation up to 4350 m before declining (Figure 5c). In contrast, rock cover had a negative effect on fire extent (Figure 5d).

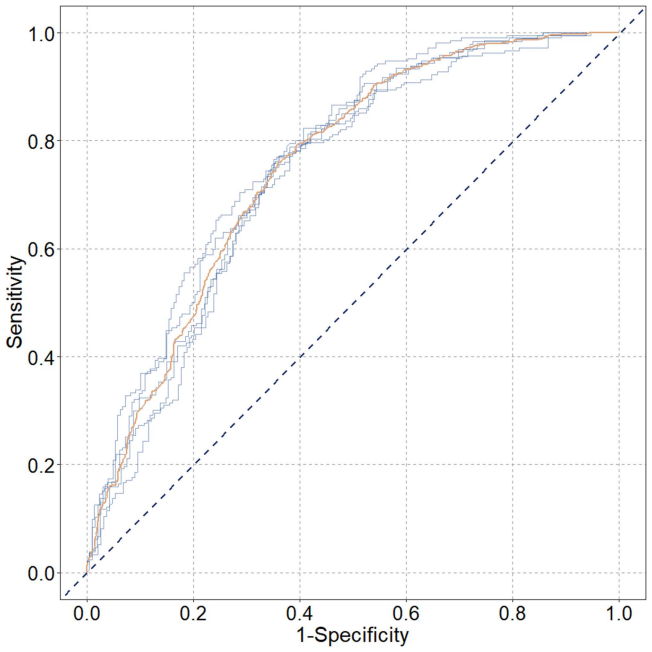

Figure 3. ROC curve of the selected GLM for modelling fire occurrence. The curve represents the average of five ROC curves obtained from five cross-validation iterations using the validation data. The orange line indicates the average curve, with a mean AUC value of 0.78 across the iterations.

Table 8. Performance evaluation of the top five GLMs for modelling fire extent. The best model is highlighted in bold.

Code	AICc	Adjusted pseudo-R^2	Coefficients significance	GVIF < 5
bn.glm.m1	679.403	0.578	Yes	Yes
bn.glm.m2	679.640	0.577	Yes	Yes
bn.glm.m7	**675.763**	**0.601**	**Yes**	**Yes**
bn.glm.m8	679.291	0.617	Yes	Yes
bn.glm.m9	681.056	0.606	No	Yes

Table 9. Summary of the best GLM (bn.glm.m7) for modelling fire extent, including estimated coefficients and significance levels for explanatory variables (linear and quadratic terms). Model performance metrics: AICc = 675.763, adjusted pseudo-R^2 = 0.601.

Variable	Estimated coefficient	Standard Error	*Z*-value	*p*-value
(Intercept)	4.440	0.110	40.368	<0.001
Elevation, 1	0.172	0.897	0.192	0.848
Elevation, 2	−3.647	0.885	−4.122	<0.001
TPI 2000, 1	4.629	0.918	5.040	<0.001
TPI 2000, 2	−2.406	0.911	−2.640	<0.001
Grass cover, 1	5.968	1.112	5.365	0.008
Grass cover, 2	−2.989	0.945	−3.165	<0.001
Rock cover, 1	1.462	1.132	1.292	0.196
Rock cover, 2	1.969	0.897	2.195	0.028

Table 10. Wald test results for the explanatory variables of the selected model (bn.glm.m7).

Variables	df residuals	Residual deviance	df	Wald test	*p*-value
Elevation	57	152.883	2	17.010	<0.001
TPI 2000	55	112.428	2	30.584	<0.001
Grass cover	53	75.370	2	32.706	<0.001
Rock cover	51	66.334	2	7.238	0.027

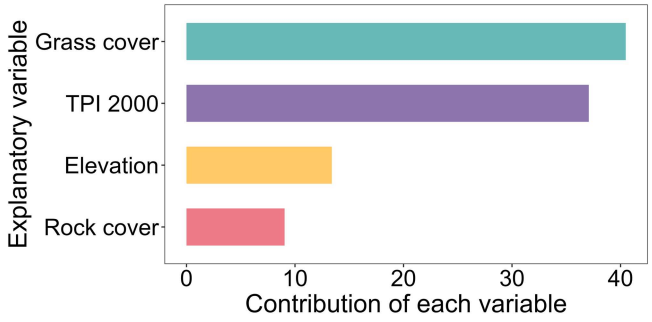

Figure 4. Relative contribution of explanatory variables in the fitted model of fire extent.

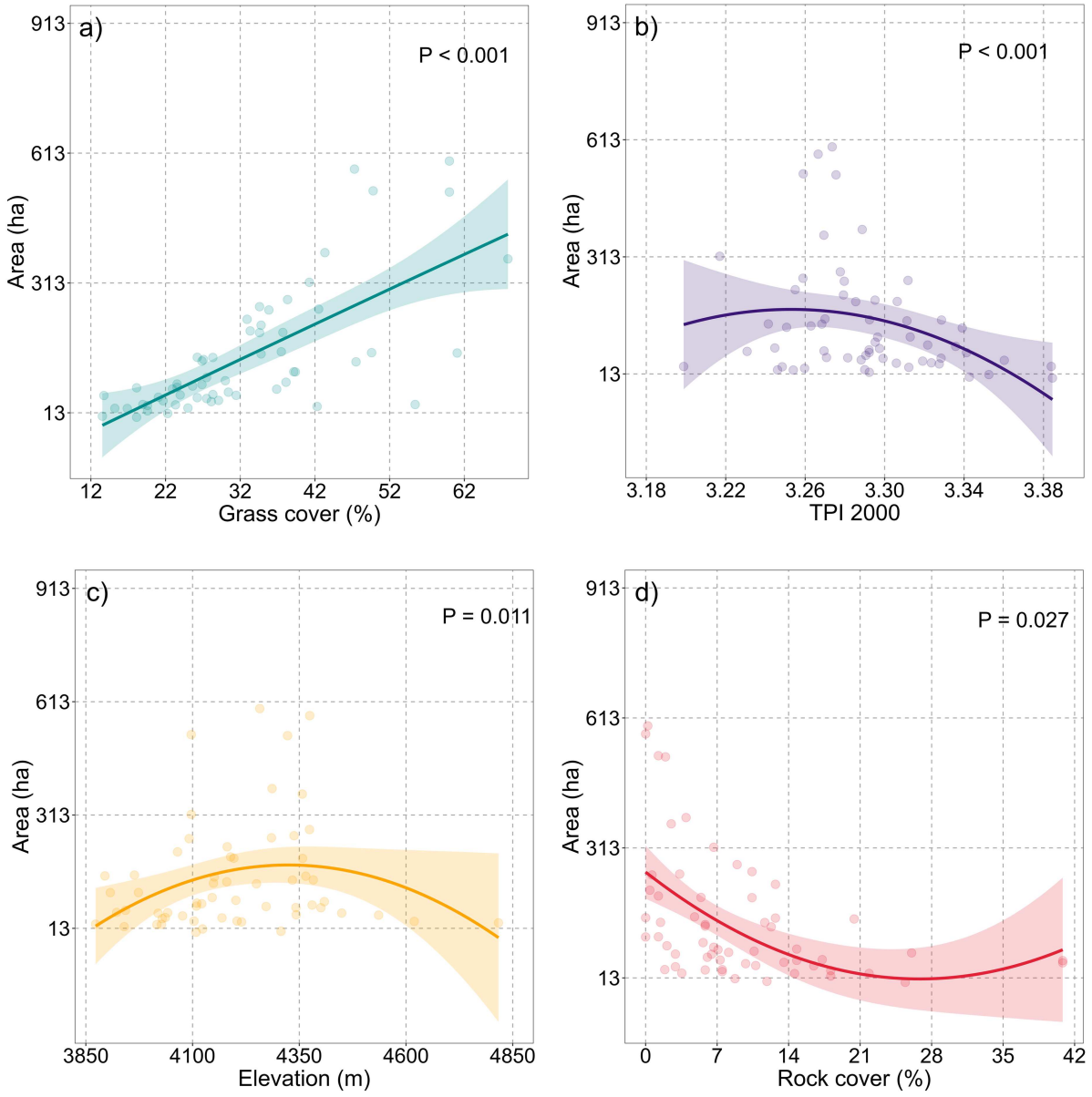

Figure 5. Relationship between grass cover (a), TPI 2000 m (b), elevation (c), and rock cover (d) with fire extent based on the best GLM (nb.glm.m7). The lines represent the variation in fire extent as the explanatory variables change. Shaded areas indicate 95% confidence interval.

Discussion

Fires pose a significant threat to biodiversity, ecosystem services, and human development (Killgore et al. 2009; Dooley and Treseder 2012; Abram 2021), underscoring the need to monitor the spatial and temporal factors that influence fire regimes. Peru is among the countries most affected by climate change (Wongchuig et al. 2018), making it essential to identify the key drivers of fire occurrence and extent. While many fires originate from human activities, both environmental and anthropogenic factors can contribute to agricultural burns escalating into large and intense wildfires. This study identified elevation, maximum temperature, SAVI, and TPI 1000 m as the primary factors influencing fire occurrence. Meanwhile, fire extent was mainly driven by grass cover, elevation, TPI 2000 m, and rock cover.

The probability of fire occurrence increased with elevation up to 4220 m, while fire extent peaked at 4350 m. These findings align with previous studies on fire occurrence in Peruvian grasslands (Zubieta 2021), particularly between July and November, which coincides with the agricultural season of rural communities (Luna-Celino and Kainer 2024). The decline in fire probability and extent above 4220 m is likely due to shifts in environmental conditions and vegetation cover. In fact, maximum temperature was also a key factor in fire occurrence, with fire probability rising until 17.26 °C, after which it declined. Several studies (e.g. Ganteaume et al. 2013; Abdi et al. 2018; Balcazar-Gallegos and Reyes-Bueno 2021; Pang 2022; Gao et al. 2023) have similarly identified temperature as a crucial driver in fire occurrence. This highlights the urgent need to integrate fire management measures into climate change strategies, as rising temperatures are one of climate change's primary impacts (Grace et al. 2002; Michelutti et al. 2015; Stevens-Rumann 2018; Jiang 2024). Unlike Zubieta (2021), who suggested the accumulated frequency of hot and dry days as an important driver of fire occurrence, our study did not identify these variables as influential. This is because the maximum temperature showed a stronger correlation with fire occurrence than the accumulated frequency of hot and dry days, which are derived from temperature and precipitation, respectively. Consequently, only the maximum temperature was considered during variable selection and model building.

Regarding vegetation, SAVI was the key factor influencing fire occurrence, while grass cover was the only significant cover class affecting fire extent. Normalised difference of vegetation index (NDVI), a similar index to SAVI, has also been identified as a determinant of fire occurrence (Abdi et al. 2018; Pang 2022). The probability of fire occurrence increased with SAVI values up to 0.15, after which it declined. This initial rise in fire probability at low SAVI values is likely due to reduced vegetation moisture during the dry season, increasing fire susceptibility (Zubieta 2021). In contrast, higher SAVI values indicate greater moisture content, which limits fire occurrence, as well as the presence of woody herbs (e.g. *Baccharis*, *Parastrephia*, *Tetraglochin*), which have lower ignitability and combustibility than grasses (Pausas et al. 2017).

The woody herbs of the altiplano are perennial, with thick leaves and a reduced leaf area—traits that make them resistant to combustion (Pausas et al. 2017). These characteristics are particularly relevant in the low-intensity fires typical of grassland ecosystems (Oliver et al. 2017; Pausas 2022; Gutierrez-Flores et al. 2024). Consequently, as these species become more dominant, fire probability declines. While woody cover was not a key factor in fire extent, correlation analysis suggests a negative association ($r = -0.12$, Appendix 2). Notably, species of the genus *Baccharis*, which can take on a shrubby form, may serve as live firebreaks—a widely used fire management strategy in various countries (Cui et al. 2019). Field observations indicate that *Baccharis* species do not fully combust during fires, though high temperatures often lead to post-fire mortality. However, burned individuals have demonstrated vegetative recovery. Conversely, grass cover had a positive relationship with fire extent, likely due to its high combustibility and ignitability. The presence of thin leaves and the retention of dead leaves (Carilla et al. 2011; Pausas et al. 2017) facilitate rapid fire spread, making grass cover a critical factor in determining fire dynamics.

In the southern Peruvian grasslands, uncontrolled agricultural burning is the primary ignition source (Luna-Celino and Kainer 2024). Fires often spread through the wind into mountainous areas (Yang et al. 2007), particularly when burning occurs in the afternoon (Alvarez et al. 2024). Due to the irregular terrain and the risks posed to the local population, fire control in these regions is extremely challenging (Yang et al. 2007), frequently resulting in extensive burned areas. Notably, the topographic position index (TPI)

was a key factor influencing both fire occurrence and extent. High and positive values—typically associated with ridges (De Reu 2013)—were linked to increased fire occurrence and larger fire extents. Ridge areas are likely to be most affected because, once ignition occurs—primarily at the base of the mountains—fires tend to spread upward due to wind and temperature gradients. This index also plays a significant role in fire severity, with ridge areas experiencing the highest levels of fire damage (Harris and Taylor 2017). In contrast, areas with greater rock cover were associated with smaller fires, as rock acts as a natural barrier to fire spread.

None of the assessed anthropogenic variables significantly influenced fire occurrence or extent. This contrasts with other studies that identified proximity to roads as a contributing factor to fire occurrence, with more fires occurring near roads (Yang et al. 2007; Narayanaraj and Wimberly 2012). However, in our study area, agricultural activities—identified as the primary ignition source (Alvarez et al. 2024; Luna-Celino and Kainer 2024)—are typically conducted in remote areas far from roads. This likely explains why road proximity was not a determining factor in our findings. Our results align with Zubieta et al. (2023a), who found that only 4% of fires are reported as emergencies to INDECI, while most remain unreported due to their remote locations. The absence of roads, combined with the rugged terrain of mountainous regions, makes fire control particularly challenging and often results in large, uncontrolled fires. Additionally, although roads may act as natural firebreaks and help limit fire spread (Buthelezi et al. 2016; Dewar 2021), this does not appear to be the case in our study area. High wind speeds facilitate fire spread by enabling flames to jump across roads, especially since rural roads in the region are narrow (personal observation).

Conclusions

In line with our objectives, this research identified key environmental factors driving the occurrence and extent of grassland fires. Grass cover and topography were critical determinants of fire spread in the Peruvian highlands, suggesting that effective fire management should combine vegetation-based strategies with the monitoring of climatic drivers. Contrary to other studies, no anthropogenic drivers commonly explored in fire occurrence and extent were statistically significant in our models. Nevertheless, other variables remain to be explored. For instance, wind direction and speed are crucial determinants of fire spread (Viegas 2004; Pimont et al. 2012; Ganteaume et al. 2013; Cannon et al. 2017) and, consequently, impact fire extent and severity. Given that the occurrence model returned an R^2 value of 0.2, further investigation and incorporation of additional variables are warranted to improve the model's ability to predict fire risk levels. Nonetheless, this study represents an initial step toward understanding the factors that influence the occurrence and extent of anthropogenic fires in regions characterised by high topographic variability. This variability highlights the importance of incorporating more local variables (e.g. microclimate, fuel moisture, cropland location) into the development of future models of fire occurrence and extent.

Advancements in remote sensing and artificial intelligence have provided valuable data and analytical tools for fire research (Agustiyara et al. 2021; Zubieta 2021; Oliveras 2014a). However, *in situ* assessments remain essential for validating and refining remotely obtained data (Pause 2016). For example, our findings highlight grass cover as the most critical factor driving fire extent, underscoring the need for targeted fire control strategies to limit fire spread. One widely adopted approach in fire-prone ecosystems is the establishment of green firebreaks (Bowman et al. 2020; Kelly 2020). Future research should focus on identifying plant species suitable for green firebreaks, considering traits such as resilience, post-fire resprouting ability, growth rate, and ease of recruitment (Cui et al. 2019).

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Author contributions

Ivon Gutierrez-Flores designed and performed the research and wrote the original draft. Angela Mercado conducted the research. Ricardo Zubieta contributed to providing HDF and DDF data and assisting with writing. Pablo Beltrán contributed to writing and helped obtain funding. Eduardo Oyague was a major contributor to the manuscript. All authors read and approved the final manuscript.

Disclosure statement

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Data availability statement

The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

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