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WILDFIRE OCCURRENCE IN CHILE: REGIONAL MODELING AND IMPLICATIONS FOR RISK MANAGEMENT

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ABSTRACT. Wildfires pose a major environmental and societal challenge, due to their link with anthropogenic activities and changing climatic conditions. This study aimed to enhance our understanding of the drivers of wildfire occurrence across continental Chile by developing robust predictive models incorporating climatic, land cover, and anthropogenic variables. We leveraged geospatial data on historical fire events, infrastructure, fuels and weather, coupled with historical fire records through Random Forest binary models to ascertain the key drivers of ignition across four distinct ecological zones: North, Central Chile, South, and the Andes. Our analysis explored potential differences between arson and unintended fires within these regions. Model validation, assessed using the Area Under the Curve (AUC), revealed significant regional variations in predictive performance. The southern and northern zones exhibited higher predictive capacity, potentially due to less complex landscapes and fewer ignition sources compared to the densely populated and infrastructure- prone central zone, which showed the lowest AUC. The Andes region displayed intermediate performance. Our results indicated that anthropogenic factors, particularly the distance to power lines, roads, and the wildland-urban interface (WUI), were consistently among the most important predictors of wildfire ignition across the majority of the studied regions. This highlights the significant impact of human accessibility and infrastructure on fire incidence in Chile. In contrast, fuel-related and climatic variables, such as Dry Fuel Moisture Content (DFMC) and its anomaly, showed generally lower importance, although their influence increased notably in the southern zone. Partial dependence plots further elucidated the distinct ways in which these key variables influenced ignition probability across different regions and between arson and unintended fires. The findings emphasize the necessity of adopting region-specific approaches in wildfire modeling and prevention strategies, acknowledging the different interactions between natural and anthropogenic factors across Chile. This research provides a fundamental understanding for future advanced modeling and targeted risk management efforts. Future research should aim to incorporate more detailed socioeconomic data to further refine predictive models and inform effective risk mitigation strategies.

Ocurrencia de incendios forestales en Chile: modelización regional e implicaciones para la gestión del riesgo

RESUMEN. Los incendios forestales representan un importante desafío ambiental y social debido a su vínculo con las actividades antropogénicas y las condiciones climáticas cambiantes. Este estudio tuvo como objetivo mejorar nuestra comprensión de los factores que impulsan la ocurrencia de incendios forestales a lo largo del territorio continental de Chile, mediante el desarrollo de modelos predictivos robustos que incorporan variables climáticas, de cobertura del suelo y antropogénicas. Se utilizaron datos geoespaciales sobre eventos históricos de incendios, infraestructura, combustibles y condiciones meteorológicas, junto con registros históricos de incendios, para construir modelos binarios de Random Forest que permitieran determinar los principales factores de ignición en cuatro zonas ecológicas distintas: Norte, Chile Central, Sur y Cordillera de los Andes. Nuestro análisis exploró posibles diferencias entre incendios provocados y no intencionados dentro de estas regiones. La validación de los modelos, evaluada mediante el área bajo la curva (AUC, por sus siglas en inglés), reveló variaciones regionales significativas en el desempeño predictivo. Las zonas sur y norte mostraron una mayor capacidad predictiva, posiblemente debido a paisajes menos complejos y a una menor cantidad de fuentes de ignición, en comparación con la zona central, densamente poblada y con alta presencia de infraestructuras, que presentó el valor de AUC más bajo. La región andina mostró un ajuste intermedio. Nuestros resultados indicaron que los factores antropogénicos —particularmente la distancia a las líneas eléctricas, carreteras y la interfaz urbano-forestal (WUI, por sus siglas en inglés)— se ubicaron de manera consistente entre los predictores más importantes de la ignición de incendios forestales en la mayoría de las regiones estudiadas. Esto resalta el impacto significativo de la accesibilidad humana y la infraestructura sobre la incidencia de incendios en Chile. En contraste, las variables relacionadas con combustibles y clima, como el contenido de humedad del combustible seco (DFMC, por sus siglas en inglés) y su anomalía, mostraron en general una menor importancia, aunque su influencia aumentó notablemente en la zona sur. Los gráficos de dependencia parcial permitieron además esclarecer las distintas formas en que estas variables clave influyeron en la probabilidad de ignición entre regiones y entre incendios provocados y no intencionales. Los hallazgos enfatizan la necesidad de adoptar enfoques específicos por región en la modelación y las estrategias de prevención de incendios forestales, reconociendo las diferentes interacciones entre los factores naturales y antropogénicos a lo largo de Chile. Esta investigación proporciona una base fundamental para futuros modelos avanzados y esfuerzos de gestión del riesgo más focalizados. Las investigaciones futuras deberían incorporar datos socioeconómicos más detallados con el fin de refinar los modelos predictivos e informar sobre estrategias de mitigación del riesgo más efectivas.

Keywords: Wildfires, Chile, Random Forest, Spatial Modeling, Risk assessment.

Palabras clave: Incendios forestales, Chile, Random forest, modelización espacial, evaluación del riesgo.

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1. Introduction

Wildfires are a key environmental agent that plays an important role in the maintenance and evolution of ecosystems and have been essential to human life since ancestral times (Castillo *et al.*, 2003). Nevertheless, anthropogenic actions and climate change are significantly modifying fire regimes, increasing burn severity and intensity, fire size, and ignition frequency (Kelly *et al.*, 2023). Globally, wildfires are a main cause of forest decline and a substantial source of greenhouse gas emissions and pollutants, which further exacerbate climate change (Urzúa and Cáceres, 2011). Wildfires are becoming a threat to the biosphere, driving degradation through the reduction of biodiversity or destruction of habitats in non-fire-prone regions, while causing extensive social and economic impacts, both directly through the loss of human lives and infrastructure, and indirectly by aggravating soil erosion, loss of ecosystem services, and water pollution (Úbeda and Sarricolea, 2016). This situation is raising concern about the impacts of wildfires from anthropogenic fire regimes (FAO and Plan Bleu, 2018).

Recently, we have witnessed some of the most dramatic and damaging wildfire seasons and episodes, exemplified by the southern California fires in January 2025, the Canadian summer of 2023, or the wildfire heat wave across Europe in 2022 (Rodrigues *et al.*, 2023a).

In Chile, the study region of this work, fires pose a major societal threat, with the so-called firestorms emerging in Central Chile in the last decade. The recent Valparaíso fire in February 2024 resulted in 137 deaths, following similar devastating events in 2017 and 2023 where single fires exceeded 100,000 hectares. This situation is projected to intensify with climate change in the coming decades. It has been estimated that in the south-central zone of Chile (31°- 45° S), rainfall will decrease by approximately 25% in spring and 40% in summer by the end of the 21st century (González *et al.*, 2011). Furthermore, temperatures are expected to increase throughout the country between 2 and 4 °C in some scenarios (CONAMA, 2006), altogether increasing fuel aridity, thus facilitating the occurrence and spread of fires. In Chile, landscape flammability, fuel availability, and the presence of ignition sources modulate the occurrence and magnitude of wildfires (González *et al.*, 2020). The intermingling of buildings and urban areas with vegetated lands, commonly known as the wildland-urban interface (WUI), also serves as a major (and growing) driver of ignition (Sarricolea *et al.*, 2020). This expansion sometimes originates from informal neighborhoods with limited resources, a phenomenon known as *'tomas'* – the occupation or takeover of land for housing.

In this context, understanding the underlying driving factors of ignition is crucial to effectively prevent wildfires and mitigate risk. The development and implementation of predictive tools, such as fire ignition models, are among the most effective approaches. Their added value lies in their ability to reveal where and how factors influence fire incidence, providing a fundamental basis for designing effective prevention strategies (Nunes *et al.*, 2016). Recent studies embody this approach. Aguirre *et al.* (2024) identified key factors for fire prediction within the particular context of the Chilean wildland-urban interface (WUI), finding that those related to their spatial disposition had an important impact. Ochoa *et al.* (2024) mapped the ignition probability and its fundamental drivers across Europe, highlighting the importance of climatic variables. Similarly, Keeping *et al.* (2024) characterized wildfire occurrence throughout the United States, seeing some spatial differences and also pointing to the importance of climatic variables, such as fuel moisture.

However, Costafreda-Aumedes *et al.* (2017) highlighted in their review the scarcity of studies in Ibero-American regions. In this context, several studies were recently conducted in Chile. One example is the work of Azócar de la Cruz *et al.* (2022), which integrates climatic, topographic, and anthropogenic factors. Although their study is limited to a specific region of Chile, it identifies the proportion of agricultural land, proximity to roads, and distance to urban areas as the most influential variables, with fuel moisture also playing a notable role. Another relevant study is that of Aguirre *et al.* (2024), which analyzes how specific housing characteristics within the Chilean wildland–urban interface contributes to wildfire vulnerability at a local scale. Nonetheless, the national focus of this research makes direct comparison with broader-scale models more challenging, as they have been adapted to the specific settings of each study region in the central sector of Chile (Aguirre *et al.*, 2024; Azócar de la Cruz *et al.*, 2022).

Our study aims to enhance the understanding of factors contributing to wildfire ignition across continental Chile. We developed a set of statistical models using Random Forest to estimate the spatial probability of wildfire occurrence. The models leveraged geospatial data on historical fires, buildings, power lines, roads, land cover, and weather. We investigated the role of ignition drivers, focusing on potential differences between arson and unintended fires, as well as regional differences across four zones: north, central, south, and Andes. We hypothesize that ignition factors will vary by region and cause, with fuel moisture content and distance to the wildland-urban interface (WUI) being primary drivers.

2. Study Area

The study region covers the full extent of continental Chile (Fig. 1). The country presents a wide array of climatic conditions due to its significant latitudinal range (spanning from 17°30'S at the Peruvian border to 56°30'S at Cape Horn), encompassing warm desert climates in the north (BWh and BSh[1]), a Mediterranean climate in the central region (Csa and Csb), and temperate-to-cold climates in the south (Cf, ET and EF) (Sarricolea *et al.*, 2016). This climatic diversity is coupled with a pronounced west-east elevation gradient from the Pacific coast to the Andes Mountains, with altitudes ranging from 0 to over 6,000 m.a.s.l. (Errázuriz *et al.*,1998), interrupted in central Chile by the Coastal Range, which creates the Chilean Central Valley. Climate conditions influence fire activity, which is highly seasonal, with the largest number of ignitions and burned area concentrated in the summer months, when weather conditions are favorable to fire ignition and spread (González *et al.*, 2020).

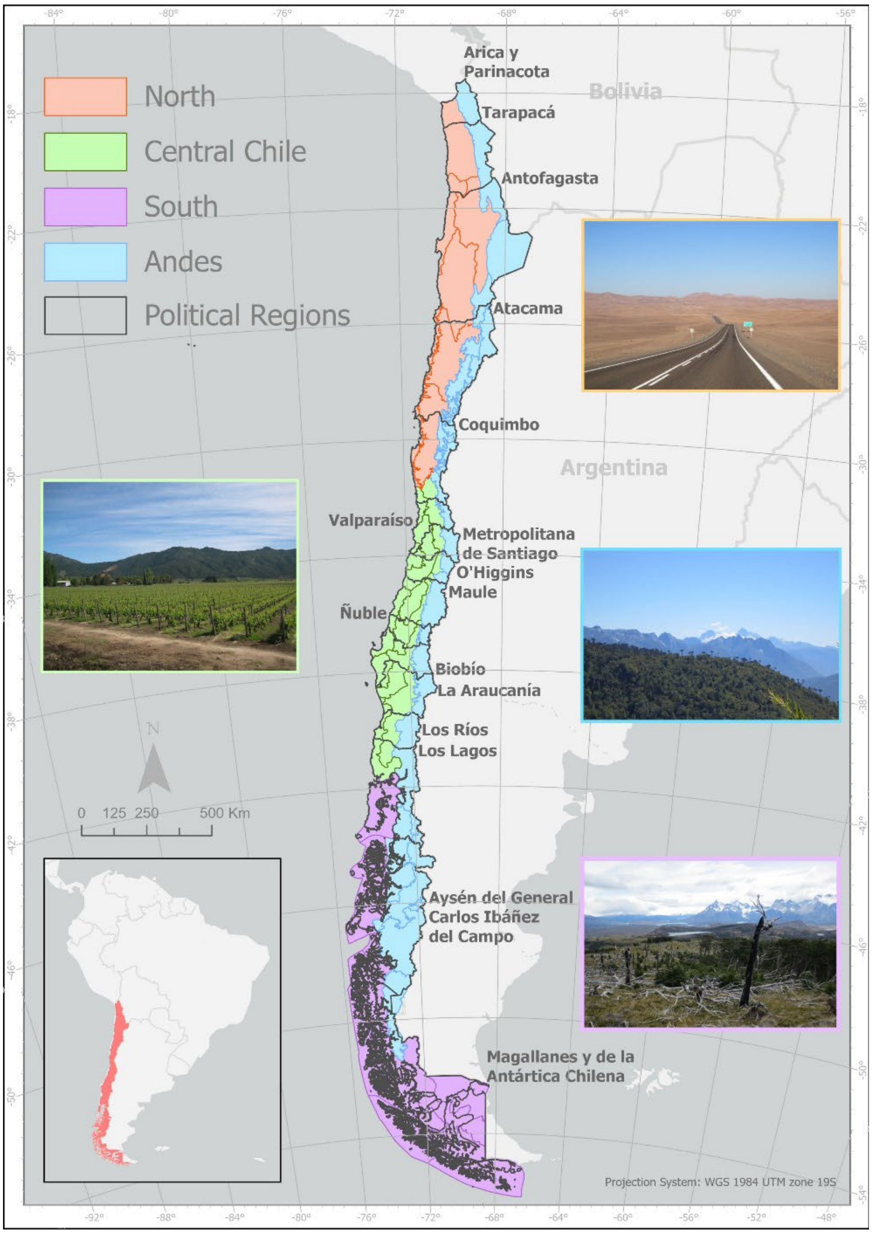

Figure 1. Spatial division of modeling zones across Chile. Color key indicates outlines the four analyzed regions. Images: Jorge Félez-Bernal.

[1] Climate codes given according to the Köppen-Geiger taxonomy.

The temperate central zone is the demographic and economic heart of the country, hosting major urban areas and the primary agricultural and forestry activities, particularly the cultivation of eucalyptus (*Eucalyptus spp.*) and pine (*Pinus radiata*) (CONAF, n.d.).

Historically, Chile's development has been rooted in the extraction of natural resource like copper, with many industrial uses; guano, used as organic fertilizer, and the production of cereals. The latter grew aggressively during the 19th and 20th centuries boosted by economic incentives to transform native forests into agricultural or grazing land (Urzúa and Cáceres, 2011) a process that increased soil erosion due to the resulting loss of vegetation. An extensive plantation policy was subsequently implemented to address the issue, resulting in the current landscape configuration. This policy had notable social, economic, and environmental repercussions, including land ownership concentration in large corporations; as a result, currently, two major companies dominate the country's forestry production (Poblete *et al.*, 2023). The expansion of plantation monocultures simplified the landscape in central Chile, particularly in the Coastal Range, which was less suitable for mechanized agriculture and even more prone to erosion. The companies' preference for contiguous land parcels resulted in vast, structurally and compositionally homogeneous industrial plantations (McWethy *et al.*, 2018). Bowman *et al.* (2019) highlighted the significant flammability of these plantations, attributing it to their dense structure and thick litter accumulation.

Eucalyptus spp. are exotic fast-growing species adapted to fire regimes, with some species exhibiting adaptations for post-fire survival and regeneration (i.e., *Eucalyptus globulus*), influencing their propagation and ecosystem dynamics. Its establishment further exacerbated wildfire risk (Fig. 2). The horizontal continuity compounds with vertical fuel ladders, as these plantations often lack understory clearing, contributing to an observed trend of increasing extreme fire seasons in terms of annually burned area (González *et al.*, 2011).

Figure 2. Eucalyptus globulus plantations in Pudá sector, Tomé commune, Biobío Region, after 'El Cortijo' fire (February 2023). Photo by Jorge Félez-Bernal (2023).

Ignition sources manifest in various ways, with power lines being an important contributor. Beyond the inherent risk of sparks, the use of uninsulated low- and medium-voltage wires substantially elevates the likelihood of fires, particularly when coupled with inadequately maintained vegetation-free corridors. In Chile, the WUI's footprint and arrangement are particularly complex, stemming largely from the urban expansion of major population settlements. According to Úbeda and Sarricolea (2016), the laxity of regulations in the past allowed the construction of these very low-quality buildings with poor infrastructure provision in these forest areas, which are often excluded from urban plans. This has resulted in a vast and intricate WUI that is challenging to study, as these unofficial neighborhoods are frequently unregistered because 'the territorial planning instruments are either outdated or do not consider preventive planning for this type of threats' (Garay *et al.*, 2019).

The accumulation of fuel within the WUI, combined with areas of high population density, creates a highly flammable environment (Úbeda and Sarricolea, 2016) (Fig. 3). Likewise, people's accessibility to flammable surfaces also boosts ignition potential, making roads and pathways important elements to consider in wildfire studies (Martín *et al.*, 2018; McWethy *et al.*, 2018; Oliveira *et al.*, 2012).

Figure 3. Wildland-urban interface zone affected by fire in areas dominated by Pinus radiata at the base of the Coastal Range, Chiguayante commune, Biobío Region. Photo by Nicolás Salazar Maleras (2021).

3. Materials and methods

3.1. Fire data and response variable

The dependent variable, fire occurrence, was created using the database of the National Forest Corporation (CONAF), which contains historical fire records from 1984 to 2023 across the entire Chilean territory. This database provides information on the location where a fire starts. Additionally, it offers supplementary information such as the start and end dates, as well as the causes of the fires (causality data is only included up to 2019).

The database attained a wide array of ignition sources. For this work, causes were aggregated into 4 major groups as follows: unintentional fires (related to agricultural and forestry work, recreation, and transit); intentional (mainly caused by economic benefits, individuals with mental health issues, or conflicts); natural fires (primarily lightning strikes and volcanic eruptions); and fires of unidentified origin. In the exploratory analysis (section 4.1) we assess the 4 groups, retaining only intentional and unintentional fires into the regression models.

A binary response variable (presence and absence of ignitions) was constructed from this information. Presence locations were retrieved from the pair coordinates recorded during 2009 to 2019 (fires smaller than 1 hectare were excluded). To obtain the non-fire data points, we constructed 10 background random samples across the region. The placement of non-fire locations was constrained to vegetated areas located 500 meters away from an ignition (to avoid corregistration) (Azócar de la Cruz *et al.*, 2022). Each "non-fire" sample was balanced to contain the same number of observations that the "fire" sample in terms of ignition cause and date (Costafreda-Aumedes *et al.*, 2017; Gelabert *et al.*, 2025).

3.2. Explanatory variables

To predict the probability of ignition, variables from different domains were selected according to the literature. We selected environmental factors related to fuel aridity like dead fuel moisture content (DFMC), DFMC anomaly, and fuel type, as found in Rodrigues *et al.* (2023b) or Oliveira *et al.* (2012); factors related to site accessibility (Martín *et al.*, 2018; Oliveira *et al.*, 2012), namely the Euclidean distance to the road network; we considered the human pressure on wildlands (Azócar de la Cruz *et al.*, 2022), modeled as the Euclidean distance to buildings; and potential sources of accidental ignitions (Sayarshad, 2023), spatialized as the distance to the power line network, calculated with GIS tools.

Among weather-related factors, DFMC was selected as it synthesizes the information of two variables, temperature and relative humidity, into a single value. The premise behind using this variable is that moisture content hinders the start of a fire by influencing the energy required for combustion. To obtain the DFMC and anomalies, data from the Copernicus Climate Change Service was used. This service provides a historical series of surface temperature and relative humidity data from the ERA5-Land Reanalysis dataset with a spatial resolution of 9km (Copernicus Climate Change Service, 2019) and an hourly temporal resolution. This allows linking the calculated data to the date each ignition occurred and grants the constructed models a dynamic nature, meaning that predictions can be generated at multiple temporal scales (daily, based on climatic aggregates, or on future projections). The type of fuel sustaining ignition was also considered. For this, the land cover map of MapBiomas Chile (MapBiomas, 2022) was used. This map provides the country's land cover and land use with a spatial resolution of 30m and is yearly updated. The 2022 map was chosen as it's the latest product and therefore likely the most accurate in the series, despite being outside the study period. From these layers, the relevant covers were extracted, which were those that could serve as fuel for an ignition: forest formations (code 1), non-forest natural formations (code 2), forest plantations, and agriculture-pasture mosaic (code 3).

Accessibility was represented by the distance to roads, based on the premise that proximity to communication routes leads to a higher probability of fire occurrence due to human transit (Leone *et al.*, 2009 and Costafreda-Aumedes *et al.*, 2017). The national road network layer from the Ministry of Public Works was used, updated to 2019. To represent the WUI, information on the distance to buildings was also extracted. Chile has experienced significant urban expansion in large cities, and this growth sometimes occurs unplanned through informal settlements (Schuster-Olbrich *et al.*, 2024). To represent this complex reality, the Microsoft Building Footprints layer, updated to 2024, was used. Its suitability for the objective of this work lies in the fact that it includes all buildings, regardless of their legal status, with a precision of 95% in South America (Microsoft, 2024). Finally, the distance to power lines was also considered. The layer used was provided by the Superintendency of Electricity and Fuels, updated to 2021. However, in this case, not all sections were used; only overhead power lines were selected and distinguished based on whether the cable was covered by protection or not.

Once the layers of power lines, roads, and buildings were obtained, the Euclidean distance was calculated. These layers were all generalized to a common resolution of 100 meters, and the value of each variable was extracted for each point.

3.3. Exploratory analysis

Before creating the model, an exploratory analysis of fire incidence was conducted to understand the broad patterns of fire incidence in the country and to select a representative temporal period upon which building our ignition probability model. The exploratory analysis sought to ensure a temporally coherent association between fire occurrence and other variables, and to verify the reliability of historical ignition data regarding their spatial and temporal location, as well as the assigned cause. We acknowledged the likely improvement in fire records over the long study period (1984-2023), which could have led to an increase in recorded fires due to enhanced data collection methods. Initially, we considered the ten-year period up to 2023 as optimal, given that during this las decades CONAF began recording precise geographical coordinates of fires. Nevertheless, data on the cause of fires were unavailable for the last four years of this range, extending up to 2019. We analyzed the annual and monthly distribution of the number and size of fires across the entire historical record and selected a period for modeling. In addition, we also considered their cause and the geographical zone.

3.4. Training and testing the ignition probability model

3.4.1. Model Calibration

The ignition probability model was trained using the Random Forest (RF) algorithm (Breiman, 2001), which allows modeling the probability of occurrence of a binary event (presence/absence of fire) drawing non-linear relationships from a set of explanatory variables (Fig. 4). This algorithm is one of the best performing and is often the preferred alternative in most fire modeling endeavors (Chicas *et al.*, 2022). The success of RF lies in its ability to handle large data sets and capture complex relationships between variables, offering robust and accurate predictions by combining the results of multiple decision trees. This has made it a popular model for predicting fires due to its flexibility and predictive power (Oliveira *et al.*, 2012).

Our ignition probability model was hence constructed using a binary classification model, which estimates the probability of a given observation belonging to the “fire” category. To do this, we calibrated 1,000 model realizations, optimizing each individual model according to the number of predictors at each split (*mtry*=2-to-4). The optimal *mtry* was estimated via repeated cross-validation with five data splits and three repetitions of the cross-validation. The number of trees in the forest (*ntree*) was constantly set at 1,000.

During the calibration process, a stratified sampling was used to ensure a balanced training set in each iteration, thus reducing the risk of overfitting. To achieve this, the data were grouped according to fuel types, geographical tile (1x1º), and biome class based in the pyromes of Luebert and Pliscoff (2022), selecting 1 “fire” and 1 “no-fire” instance for each combination of classes. This strategy ensured that the sample was representative in terms of fuel type and geographical settings while contributing to minimize spatial autocorrelation in the residuals (see also section 3.4.2). This procedure was repeated across the 8 combinations resulting from 2 ignition causes and 4 major geographical regions. All analyses were carried out using the *caret* R package (Kuhn, 2008; R Core Team, 2023).

3.4.2. Model testing and performance

Each of the 1000 candidate models underwent validation to estimate its predictive accuracy. Test samples were extracted from the pool of records not used during calibration, using the same stratified sampling approach. For each model, we calculated the Area Under the Curve (AUC), a widely used, threshold-independent metric that quantifies classifier performance on a scale from 0.5 to 1. An AUC of 0.5 indicates random prediction, signifying a completely unreliable model, while an AUC of 1 represents perfect prediction. As a guideline, a minimum AUC of 0.70 is often considered acceptable (Zhou *et al.*, 2011). AUCs were calculated for each combination of ignitions source and geographical region.

We also analyzed the spatial autocorrelation of the predictive model residuals using the global Moran's I index. This step was crucial because the presence of spatial autocorrelation would suggest that the model inadequately captures the spatial structure of the fire phenomenon, indicating that it fails to account for spatial relationships within the data, potentially due to missing independent variables. Only models with no significant spatial structure in their errors ($p > 0.05$) were submitted to interpretation and variable importance estimate.

3.4.3. Variable importance and explanatory sense

In addition to the model's ability to correctly predict fire occurrence, the contribution of the considered predictive variables and their explanatory sense have been evaluated. Once the importance of these variables was obtained, a box and whisker plot were constructed to visualize the weight of each variable in the models.

To complete the study of the variables, an analysis of the variables with PDP (Partial Dependence Plot) was also performed to understand how a specific variable act within a complex model. To obtain the PDP and the importance of the variables, it was first necessary to choose a representative model, which was selected based on the AUC extracted previously, choosing the model with the AUC value closest to the median of the set of models.

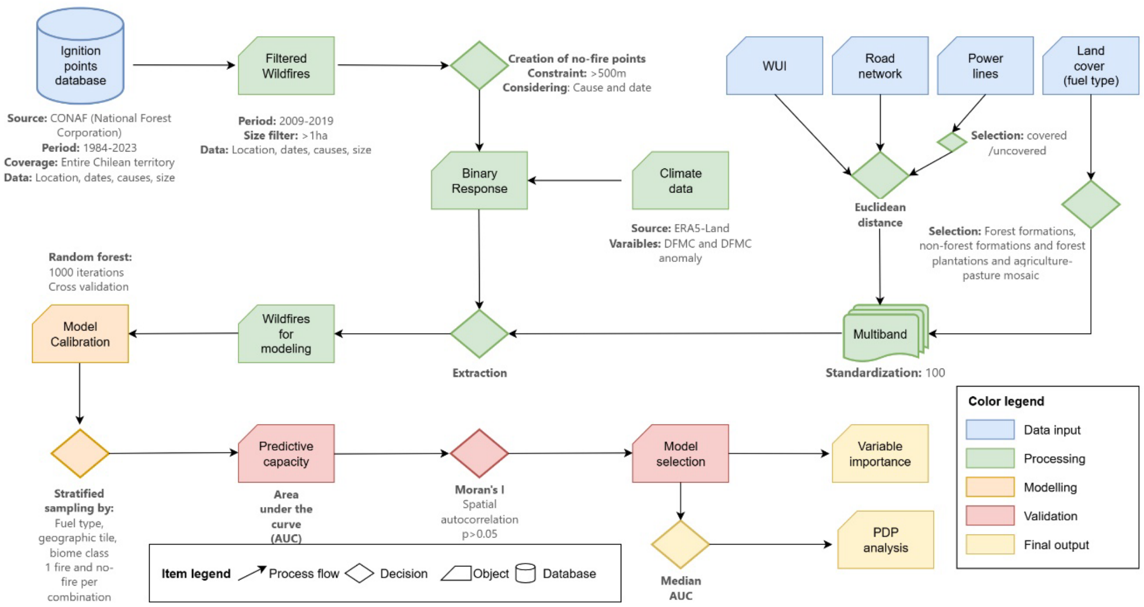

Figure 4. Methodological workflow followed for modeling fire ignition probability.

4. Results

4.1. Exploratory analysis

Since 1984, 229,813 fires have been documented in Chile, affecting 3,163,720.3 ha, with an annual average of 5,745 (±1,280.9σ) fires and 79,093 (±92,262.7σ) ha burned. Annual fire occurrences and burned area are distributed relatively evenly throughout the recorded period. Nevertheless, 2017 and 2023 stand out against this trend, with notably larger burned areas than the other seasons (512,876.6 ha in 2017 and 383,272.7 ha in 2023). These years also coincide with the local minimum in the number of fires (4,863 in 2017 and 4,448 in 2023) (Fig. 5, Table 1).

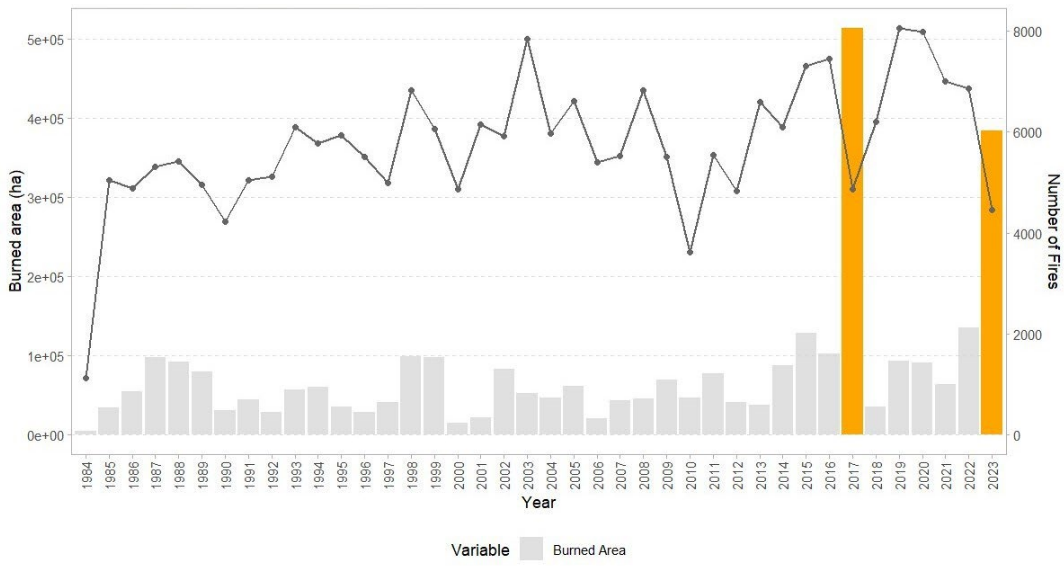

Figure 5. Yearly evolution of burned area (filled bars) and number of fires (solid dotted line). Orange bars mark the 2017 and 2023 fire storms.

Table 1. Summary of fire incidence across Chile. N, number of fires; BA burned area (ha); P95, 95th percentile of fire size. Shaded cells represent fire count data whereas italics represent the percent contribution of each cause to the total number of fires and burned area output. Summer corresponds to December, January, and February.

	Zone	North	Central Chile	South	Andes	**Total**
2009-2019	N	738	60,214	717	1,557	**63,226**
	% in summer	63	63.5	72.5	59.1	**63.45**
	Arson	0.5	98.45	0.17	0.88	**22,659**
	Natural	0	53.78	0.4	45.82	**251**
	Unintended	1.16	94.58	1.57	2.69	**36,533**
	Unknown	5.31	85.09	2.72	6.87	**3,783**
	BA	3590.5	1,114,740.8	6,069.4	85,279.1	**1,209,679.8**
	% in summer	59.7	87.5	86.9	71.3	**86.24**
	Arson	0.08	98.26	0.09	1.57	**357,948.4**
	Natural	0	35.35	0	64.65	**13,063.5**
	Unintended	0.35	87.6	0.87	11.18	**586,259.8**
	Unknown	0.5	97	0.25	2.25	**252,408.2**
	Mean size (ha)	4.52	35.2	5.85	47.5	
	P95 (ha)	14.5	24.74	17.86	150.77	
	Largest (ha)	350	159,812.6	1900	17,606	
1984-2019	N	1,774	189,024	3,316	5,787	**199,901**
	% in summer	62.7	66.8	79.3	63.9	**66.92**
	Arson	0.33	97.80	0.72	1.15	**64,737**
	Natural	0	54.52	0.46	45.01	**431**
	Unintended	0.83	93.89	1.87	3.41	**112,344**
	Unknown	2.78	89.33	3.35	4.54	**22,389**
	BA	7,491.3	2,171,305.8	76,219.9	217,939.5	**2,472,956.5**
	% in summer	60.2	82.1	94.5	75.9	**81.88**
	Arson	0.08	96.15	0.22	3.54	**668,619.1**
	Natural	0	73.96	0	26.04	**33,227.6**
	Unintended	0.35	84.73	3.16	11.76	**1,304,167.7**
	Unknown	0.51	85,42	7,18	6,89	**466,942.1**
	Mean size (ha)	3.74	36.3	16.9	37	
	P95 (ha)	11.95	14.26	12.95	94.12	
	Largest (ha)	350	159,812.6	16,760.7	25,389	

Between 1984 and 2019, a total of 199,901 wildfires were recorded in Chile (Table 1), affecting a cumulative area of 2,472,956.52 hectares. During this period, 2017 stands out for experiencing a significantly larger burned area than any other year, despite coinciding with a local minimum in the number of fires— contrasting with the general trend where years with more extensive burned areas tend to also show higher fire counts. Additionally, the largest wildfire on record occurred in 2017, burning 159,812.6 hectares.

Focusing on the period 2009-2019, the total number of fires was 63,226, with an annual average of 5,764.27, which is higher than the average of 5,497.84 for the preceding period from 1984 to 2008. Differences are also observed in fire size, with the average fire size for 2009-2019 being 19.07 ha, compared to 9.2 ha for the earlier range of years. Notably, fire incidence is concentrated during the summer months, with this pattern being most pronounced in the central and southern zones, particularly regarding burned area.

Regarding the causes, throughout both periods (1984–2019 and 2009–2019), most fires were caused by accidents, followed by intentional ignitions, while natural fires rank last, accounting for a very small share. Regionally, clear differences emerge, with wildfires primarily concentrated in the central zone of the country, followed by the Andean region. Remarkably, this central predominance is less pronounced in the case of natural fires, a large proportion of which occurred in the Andes (45.82% between 2009-2019 and 45.01% between 1984-2019). In contrast, the northern and southern zones report significantly fewer wildfires in both periods (738 and 717 respectively), with accidental fires predominating and, notably, no natural fires recorded in the northern region, although a significant number of fires have unknown origins (1.16%).

Concerning the affected area, unintentional fires continue to dominate, followed by intentional ones. Nonetheless, during 2009–2019, the Andes concentrate the majority of the area affected by natural fires (64.65%). When analyzing the average wildfire size over the entire period, both Central Chile and the Andes show similar and notably higher averages (35.2 and 47.5 respectively) than the northern and southern zones (4.52 and 5.85). Even so, for the analysis period, the Andes exhibit the highest average burned area. In this regard, the 95th percentile is particularly illustrative: in both periods, the highest value is found in the Andes, while the figure for Central Chile is closer to those of the north and south. Nonetheless, it is in the central zone where the largest recorded wildfire occurred, vastly exceeding those in other regions.

4.2. Model performance

Model performance after filtering out those exhibiting spatial autocorrelation in their residual distribution (see Table S1 for a summary of number of models without autocorrelation), varies greatly by region and, to a lesser extent, between arson and unintended cause (Fig. 6). For the northern zone of the country, the average AUC value is very high in both cases, only surpassed by the models of the southern zone. The AUC for arson (0.934) is higher than the average for non-intentional fires (0.911). The central zone records the lowest AUC values, with the models for intentional fires being slightly better than those for non-intentional fires, with averages of 0.679 and 0.67, respectively. Regarding the south, the predictive capacity for fires is much higher than in the center, also being the highest for all zones defined in this work. Again, on average, the AUC is lower for non-intentional fires. Finally, the Andes zone also shows differences in the AUC values between intentional and non-intentional fires. Although unintended fires have a higher AUC, being the only case where this occurs, the maximum value is recorded for intentional fires with 0.919 (Table S2).

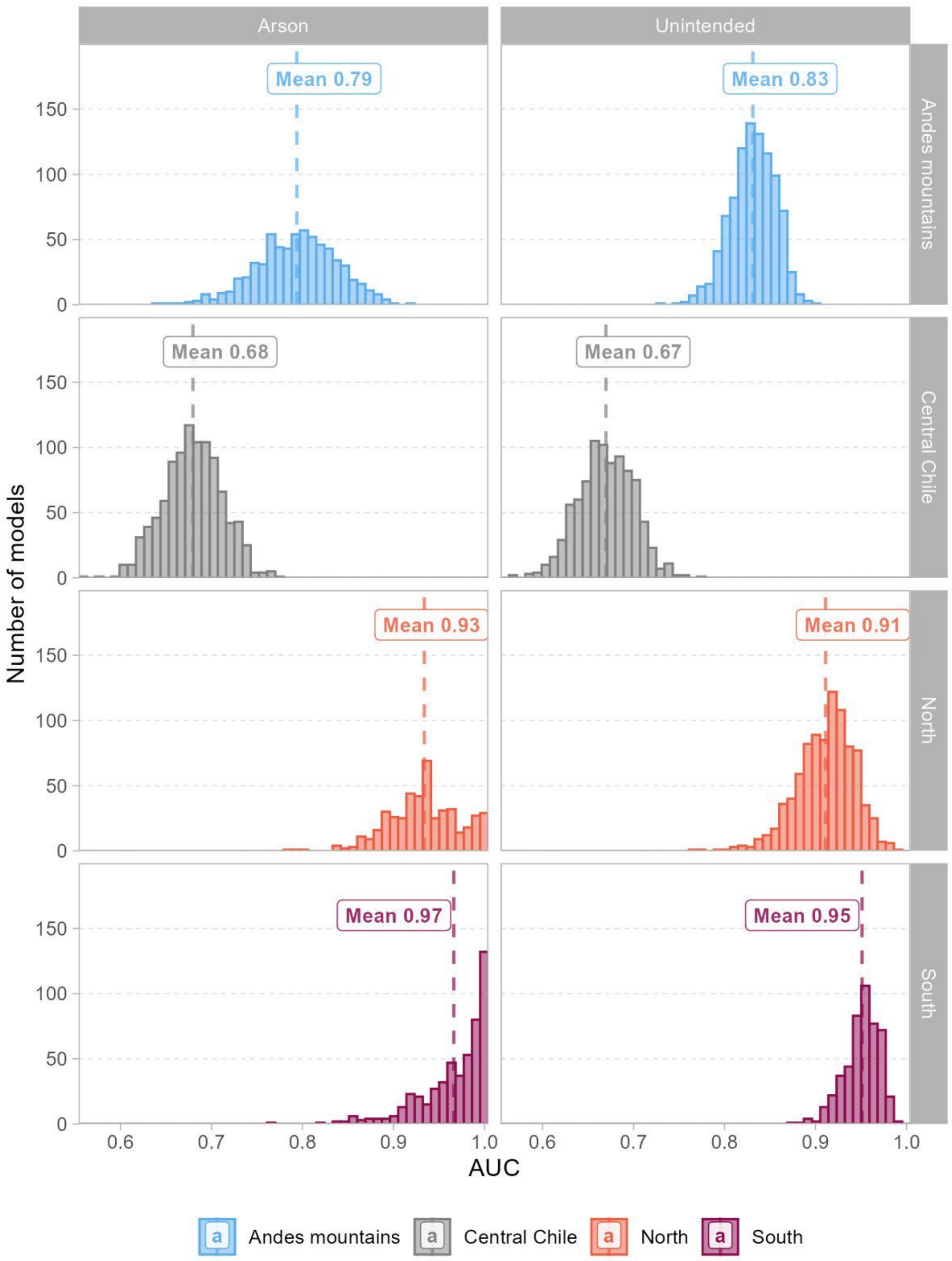

Figure 6. Summary of model validation by region and cause. Histograms show the frequency distribution of AUC values calculated from the validation samples across the 1000 models per combination.

4.3. Importance of Variables and PDP

The contribution of the drivers of ignition featured large regional differences and minor variations by cause (Fig. 7). The distance to power lines emerges as the most important variable in nearly all models, with the exception of the southern zone. It is the most influential variable for intentional fires in the northern and Andes zones, and for non-intentional fires in the central zone. Unprotected power lines also rank among the most important variables.

Road proximity shows consistently high importance for both fire causes across all regions, with a slightly greater relevance for non-intentional fires. Models for unintended fires display attributed the highest importance to accessibility by road in the south and north regions, whereas it contributes largely to model arson fires in Central Chile. The distance to the wildland-urban interface is also a key factor across all regions and fire causes, generally being a more relevant predictor in non-intentional fires. DFMC attains moderate importance across models, but its influence greatly varies by region. It is least relevant in the north, while in the south, especially for intentional fires, it becomes one of the top influential factors.

A similar pattern is observed in intentional fires in the Andes. The DFMC anomaly variable, though slightly less important than raw DFMC, follows a similar pattern. It is most influential in the central zone and in intentional fires in the south. Fuel types consistently register the lowest importance across all variables, though its significance varies by region. In the central zone, agricultural and silvicultural areas carry more weight, while in the Andes, their contribution is marginal. In the north and south, shrublands and plantations hold similar relevance across both fire causes, with a slightly higher importance of agricultural fuels for non-intentional fires in the north.

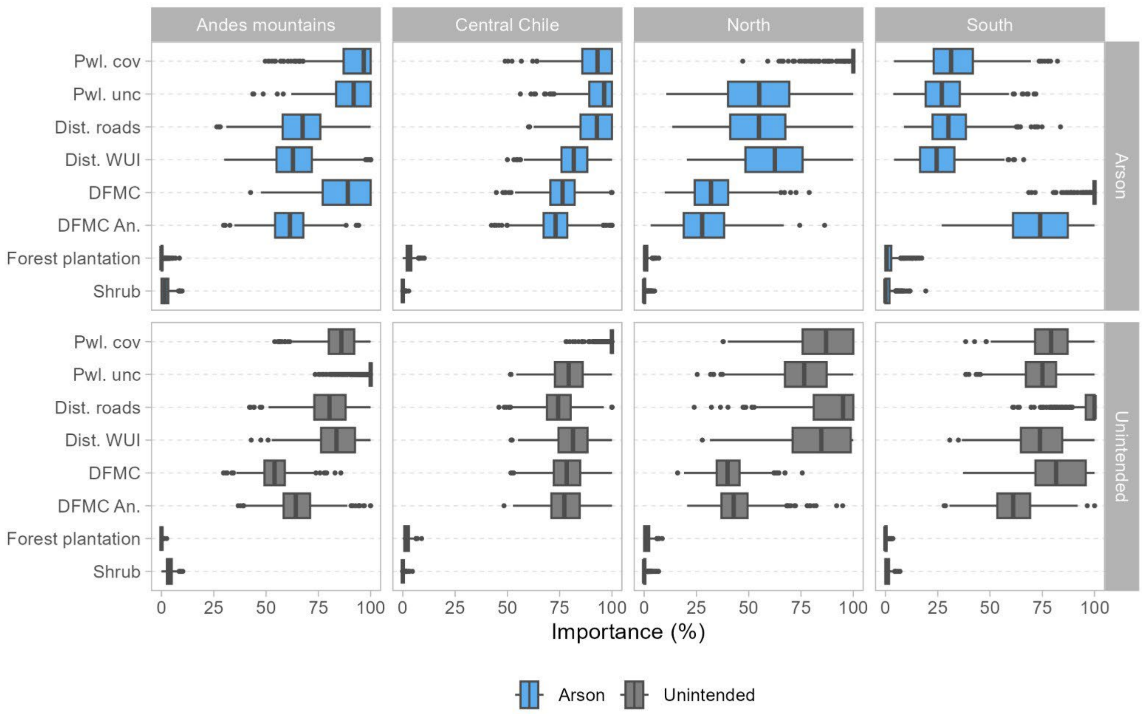

Figure 7. Variable importance by region and cause. Boxplots showing the distribution of variable importance (%) for models predicting arson (blue) and unintended (grey) wildfires across different regions of Chile.

In terms of explanatory sense, we observed a similar pattern across variables. Distance-based predictors (roads, WUI and power lines) displayed the expected sharp and inverse profile, meaning the closest to one of these infrastructures, the higher the chance of ignition. Similarly, DFMC-based drivers indicate higher probability of ignition under dry conditions, i.e., low moisture content and abnormally low DFMC (Fig. 8).

There are noticeably exceptions to these overall profiles. Given their lowest importance, the profiles of WUI draw a rather "flat" profile in arson fires in the south and power lines in unintended fires. In turn, DFMC in the north displays distinct profiles. In arson fires, DFMC draws a V-shaped line, and so does the anomaly. In unintended fires, the profile is positive, indicating a lower chance of ignition under moister conditions.

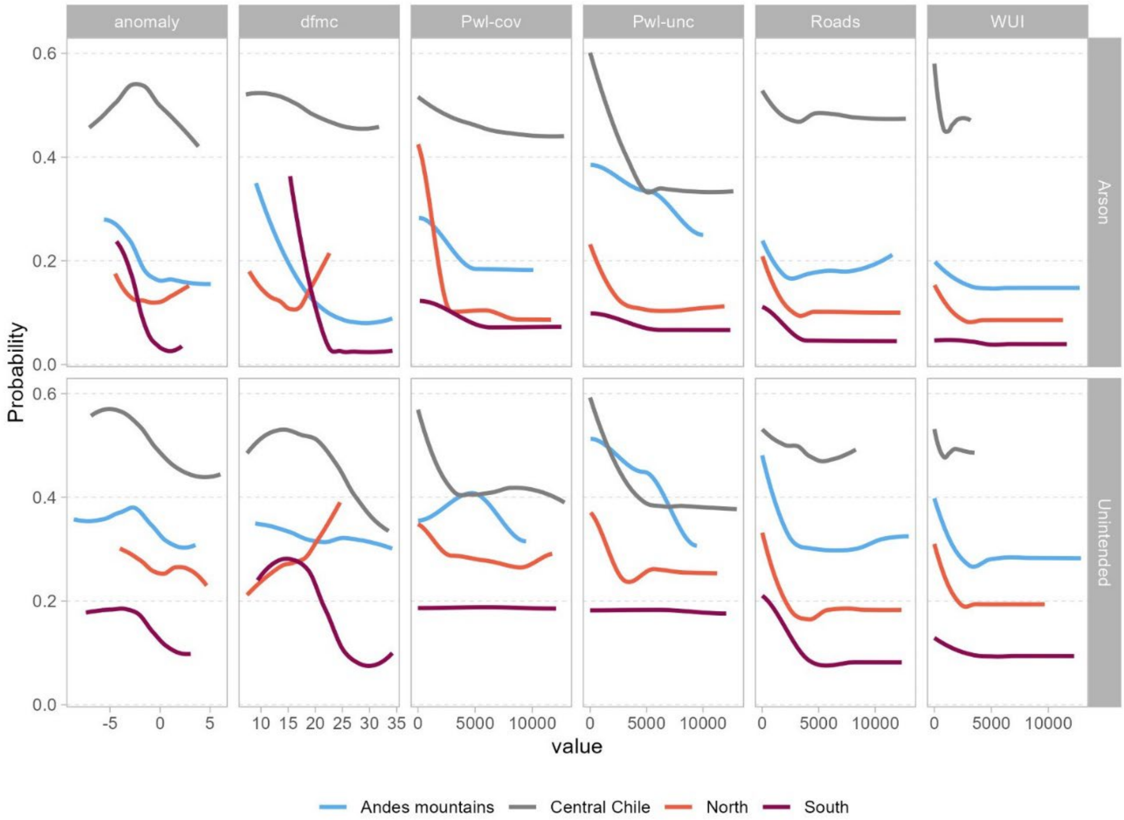

Figure 8. Partial dependence of wildfire probability by region and cause (based on median AUC representative model).

5. Discussion

In regions characterized by high fire incidence, the development of robust fire models is of paramount importance for advancing both theoretical understanding and practical application. Models enable the precise identification of areas exhibiting heightened vulnerability to fire damage, thereby facilitating evidence-based decision-making in territorial planning (Aguirre *et al.*, 2024); while elucidating the underlying causal mechanisms, provide solid insights into the factors exerting the most significant influence on fire initiation (Keeping *et al.*, 2024).

The vast majority of wildfires in Chile result from human activity, a pattern consistently reported in the literature (Castillo *et al.*, 2015; González *et al.*, 2020; Úbeda and Sarricolea, 2016) and also observed in other regions such as Portugal (Nunes *et al.*, 2016) and California (Chakraborty and Composto, 2022). In contrast, naturally ignited fires account for only a small fraction, both in terms of frequency and affected area. Jaksic and Fariña (2015) argue that fire is not an inherent part of the natural dynamics of Chile's native ecosystems.

Our featured models displayed strong regional differences in their capability to predict and explain the drivers of ignition (Fig. 7), with the southern and northern regions exhibiting higher predictive capacity. The superior performance in these regions (AUC≈0.90) may be attributed to their lower fire occurrence but also to the less dense road and power line networks in the north, and the sensitivity to weather anomalies in the south, altogether facilitating establishing causal links. The Andes region also attained a high AUC, in line with the study by Bianchi *et al.* (2023).

In contrast, the central zone records the lowest average AUC values (0.68), slightly below the 0.7 threshold. This area is characterized by a dense presence of infrastructure, including buildings, power lines, and roads. Model's performance in this region is noticeably lower than that reported in the literature, e.g., by Azócar de la Cruz *et al.* (2022), Bjånes *et al.* (2021), and McWethy *et al.* (2018). This discrepancy is likely to be related to the need of more variables or our strict sampling procedure aimed at minimizing spatial autocorrelation in the error of the model. Central Chile is highly prone to autocorrelation since fire occurrences concentrate along human infrastructure. Together with the large number of fires, it recommends caution in model calibration to avoid overfitting and autocorrelation. The presence of autocorrelation, among other effects, may artificially boost model performance (Guélat *et al.*, 2018).

In the northern zone, the distance to power lines (both covered and uncovered) emerged as one of the most influential variables, particularly for intentional fires. Power lines might play a dual role, being a potential ignition source due to sparks, but also acting as a proxy for accessibility, as power lines often follow or intersect with paths and roads used for deploying and maintenance. The distance to roads also ranked among the most important drivers, posing a similar threat to power lines. Moisture content showed the least impact in this region, likely due to the persistently arid conditions. In fact, our relationship profiles (Fig. 8) might indicate positive feedback between water availability and fires, meaning that under desertic conditions ignition is fuel-limited - favorable weather conditions increase the availability of fuels, hence fires become more likely. The relevance of DFMC anomalies was low and highly variable, consistent with the region's aridity. In fact, obtained relationship profiles might indicate positive feedback between water availability and fires, meaning that under desertic conditions ignition is fuel-limited. Fuels consistently showed the lowest importance, with their role in spatial fire modeling being secondary.

For central Chile, the distance to power lines was, again, the most important variable for non-intentional fires, while also being significant for intentional fires, although to a lesser extent. The proximity to the WUI held significant weight, especially for non-intentional fires, as highlighted by the increase in fire activity in WUI areas tied to routine human activities that can lead to accidental ignitions (McWethy *et al.*, 2018). The expansion of informal urban settlements ("tomas") poses a growing challenge, requiring specific prevention plans that address community engagement and fire safety practices such as the establishment of basic firebreaks or fuel reduction zones at the periphery of these settlements where they interface with wildlands (Prior and Eriksen, 2013).

In this context, numerous works emphasize the importance of the socioeconomic characterization in peripheral neighborhoods (Garay *et al.*, 2019; Garfias *et al.*, 2012), which are relevant in fire occurrence (Aguirre *et al.*, 2024; Sarricolea *et al.*, 2020). DFMC supported dry conditions as a driver of fire ignition in this region. The importance of DFMC anomalies increased in central Chile, reflecting the sensitivity of this area to periods of unusually low humidity. Regarding fuels, agricultural areas and plantations were more influential, likely because they are widespread and highly flammable, especially pine and eucalyptus plantations, though their importance remained lower than what had been found in other studies (Peña and Valenzuela, 2008).

In the Andes, the distance to power lines showed moderate influence for intentional fires. DFMC exerted a large influence for intentional fires, suggesting that arsonists might exploit periods of low moisture to ignite fires. Fuels consistently showed the lowest importance across this region as well.

Southern regions showed a sharp increase in DFMC's importance, aligning with Jaksic and Fariña (2015) and Kitzberger (2015) that emphasize the critical role of low fuel moisture in fire behavior. The DFMC anomaly is more important for intentional fires and showed high variability in this region. Fuels maintained their secondary role in spatial fire modeling.

Despite regional variations, certain patterns emerged consistently across Chile. The proximity to the WUI held significant weight in most models, especially for non-intentional fires, reflecting the documented increase in fire activity in these areas (Castillo *et al.*, 2015). The overall influence of DFMC anomalies was lower than that reported in southwestern Europe (Rodrigues *et al.*, 2023b), suggesting different climatic drivers or fire regimes between regions. Fuels consistently showed the lowest importance across all regions and fire causes (Table S3). This doesn't imply they are unimportant, but rather their role in spatial fire modeling is secondary compared to anthropogenic factors and moisture conditions.

6. Conclusions

This study examined fire occurrence models across four zones of Chile, highlighting key spatial and causal differences in wildfire dynamics. The initial exploratory analysis revealed marked interannual variability due to recent extreme fire seasons. Model validation using AUC scores showed regional differences in predictive performance—lower in the central zone due to its high complexity and greater in the south, likely due to simpler landscapes and fewer ignitions. The Andes showed intermediate performance, influenced by a mix of factors including varied topography and human activity concentrated in valleys.

Among predictors, proximity to power lines, roads, and the wildland–urban interface (WUI) consistently ranked as highly important, reflecting the central role of human access and activity. In contrast, fuel-related and climatic variables (such as DFMC and its anomaly) were generally less influential, though they gained relevance in the southern zone. Partial dependence plots helped interpret how these variables influenced ignition probability across zones and fire causes, revealing clear geographic and behavioral stratification. These findings emphasize the importance of considering both natural and anthropogenic factors in fire modeling and underscore the need for region-specific approaches.

This work provides a foundation for advanced fire modeling and targeted risk management in Chile. Nonetheless, the study's limitations, particularly regarding data quality and spatial resolution, highlight the need for continued research. Future work should incorporate socioeconomic variables and seek finer temporal detail to enhance prediction, especially under evolving climate scenarios.

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Supplementary Material

Table S1. Summary of models without autocorrelation.

Number of models without autocorrelation (/1000)		
Moran	Arson	Unintended
North	460	904
Central Chile	990	888
South	513	485
Andes	661	946

Table S2. Descriptive statistics of AUC across regions and causes.

Arson			
AUC	Minimum	Mean	Maximum
North	0.786	0.934	1
Central Chile	0.559	0.679	0.773
South	0.764	0.966	1
Andes	0.642	0.794	0.919
Unintended			
North	0.766	0.911	0.986
Central Chile	0.566	0.67	0.77
South	0.875	0.951	0.992
Andes	0.733	0.831	0.901

Table S3. Marginal effects of fuel types across regions and causes.

Zone	Arson			Unintended		
	Forest formations	Non-forest natural formations (shrublands)	Crops and plantations	Forest formations	Non-forest natural formations (shrublands)	Crops and plantations
North	0.129	0.133	0.133	0.262	0.253	0.289
Central Chile	0.513	0.529	0.48	0.51	0.544	0.482
South	0.048	0.035	0.07	0.127	0.129	0.13
Andes	0.178	0.165	0.2	0.339	0.309	0.318