Villagra *et al. Ecological Processes* (2024) 13:5
https://doi.org/10.1186/s13717-023-00481-6

Ecological Processes

RESEARCH Open Access

Spatial and temporal patterns of forest fires in the Central Monte: relationships with regional climate

Pablo Eugenio Villagra[1,2*], Erica Cesca[1], Leandro Manuel Alvarez[1], Silvia Delgado[1] and Ricardo Villalba[1]

Abstract

Background Natural and anthropogenic wildfires burn large areas of arid and semi-arid forests with significant socio-economic and environmental impacts. Fire regimes are controlled by climate, vegetation type, and anthropogenic factors such as ignition sources and human-induced disturbances. Projections of climate and land-use change suggest that these controlling factors will change, altering fire regimes in the near future. In the southern Central Monte, Mendoza, Argentina, the factors that modulate the fire temporal and spatial variability are poorly understood. We reconstructed the fire history of southeast of Mendoza from 1984 to 2023 and investigated the relationships between fire extent and climate variability at seasonal and interannual scales. Burned areas were determined using Google Earth Engine by processing Landsat 5-TM, Landsat 7-ETM+, and Landsat 8-OLI-TIRS sensor imagery.

Results The region exhibited high spatial and temporal variability in fire occurrence, being a mosaic of areas with different fire histories and recovery times. Between 1985 and 2023, fire recurrence ranged from sites unburned to sites with up to 14 fires. The occurrence of large fires was strongly favored by a combination of a year with abundant spring–early summer precipitation, which favors fuel accumulation, followed by a year of low spring–early summer precipitation. Precipitation and burnt area showed a very pronounced 6–7 year cycle, suggesting a dominant climatic control on fire occurrence.

Conclusions Fire distribution in southeastern Mendoza forests is not homogeneous, resulting in a mosaic of patches with different fire histories. This heterogeneity may be related to vegetation patterns and land use. The temporal variability of fires is strongly influenced by climate variability, which would promote fuel production and subsequent drying. Large fires are concentrated in periods of high interannual precipitation variability. Climate change scenarios predict an increase in temperature and precipitation variability in the region, suggesting future changes in fire dynamics. Our results contribute to the development of fire guidelines for southeastern Mendoza forests, focusing on periods of wet years followed by dry years that favor fire occurrence and spread.

Keywords Fire recurrence, Fire mapping, Recovery time, Climate, Dry forest, Wildfire

Background

Fire has been a frequent disturbance in numerous ecosystems for millions of years, long before human activities affected natural fire regimes. Thus, fire has been a very important component in evolutionary processes and a fundamental driver of the dynamics of many ecosystems (Scott 2000; Korb et al. 2012; Giorgis et al. 2021). Recent studies highlight the interactions between climate, vegetation, and human activities on fire dynamics, suggesting

---

*Correspondence:
Pablo Eugenio Villagra
villagra@mendoza-conicet.gob.ar
[1] Instituto Argentino de Nivología Glaciología y Ciencias Ambientales–CONICET-CCT Mendoza, Avda Ruiz Leal S/N, 5500 Mendoza, Argentina
[2] Facultad de Ciencias AgrariasUniversidad Nacional de Cuyo, Chacras de Coria, M5528AHB Mendoza, Argentina

that increased biomass leads to an increase in these events in regions with climatic constraints on fuel generation (Forkel et al. 2019). In some forests, fire is a vital process of ecological dynamics, accelerating successional phases, allowing the establishment of new species and reducing intra- or interspecific competition (Defossé and Urretavizcaya 2003; He et al. 2019). In other cases, however, wildfires can transform forest cover into degraded shrublands or grasslands (White et al. 1985; Cesca et al. 2014; Archibald et al. 2018).

The fire regime of an area is controlled by the atmospheric conditions at the time of fire occurrence, the long-term climate, the type of fuel-producing vegetation, and anthropogenic constraints related to ignition sources and disturbance history (Pausas et al. 2004; Krawchuk and Moritz 2011; Fischer et al. 2015; Archibald et al. 2018; Mishra et al. 2023). Meteorological factors that determine fire occurrence are related to recent variations in temperature, precipitation, humidity, and wind speed, as well as the occurrence of lightning. Changes in these climatic parameters, combined with fuel moisture levels and the natural susceptibility or adaptation of vegetation to ignition and flammability, influence fire spread (Pausas et al. 2004; Archibald et al. 2018). Variations in weather conditions determine the timing and average duration of the fire season (Fischer et al. 2012, 2015), as well as the amount of energy released during fires (Brooks and Matchett 2006; Pricope and Binford 2012). On longer time scales of centuries to millennia, climate largely determines the characteristics and distribution of plant communities, with seasonal to interannual variations in climate controlling fuel accumulation and drying, ignition, flammability, and associated fire behavior.

The Intergovernmental Panel on Climate Change (IPCC 2021) has developed climate projections for greenhouse gas emissions based on scenarios of future economic, demographic, and technological growth (Nakicenovic et al. 2000). In the western part of southern South America, the projections show an increase in temperature and consequently in climatic conditions favorable to fire occurrence (IPCC 2021). For Argentina, climatic models project an average warming of 1.5 and 4 °C for the period 2080–2099, depending on seasonality and emission scenarios, with an average increase in annual temperatures of 2.5 °C (IPCC 2021). In addition, projections show a 5–30% increase in summer precipitation for the Chaco-Pampa plains, along with a smaller increase in the length of the rainy season (Labraga and Villalba 2009). These climatic changes may affect agriculture, biodiversity, and aquatic habitats, including changes in fire frequency and intensity. Understanding the climatic factors that modulate fire regimes will allow estimation and assessment of the effects of temperature and precipitation increases on fire regimes at local and regional scales (Flannigan et al. 2005).

The southeastern area of Mendoza Province, located in the Central Monte desert, is characterized by highly variable precipitation with annual totals between 300 and 400 mm and a mean annual temperature of about 15 °C under a predominant S-SE wind regime. The vegetation is a mosaic of open forests, shrublands and psammophilous grasslands (Villagra and Alvarez 2019), and represents one of the areas with the highest fire frequency in the Central Monte region (Villagra et al. 2009). Records from the National Fire Management Plan show that fires in this area originate from anthropogenic (negligent or intentional) and natural (thunderstorms) causes. Cesca et al. (2014) showed that fire controls vegetation physiognomy, leading to a simplification of vegetation structure and loss of woody layers.

Historical records suggest a close relationship between fire and climatic conditions in the region. For example, Loggio (1992) reported the burning of 560,000 ha in General Alvear (southeastern Mendoza) during the particularly dry spring–summer of 1986–1987, which followed two years of above-average rainfall. The National Meteorological Service reported an increase in annual thunderstorms at the San Rafael weather station from 30.3 in the 1961/1970s to 39.8 in 1971/80 and 46.1 in 1981/90. Although these types of observations have been discontinued, recent work by Rasmussen et al. (2014) and DiGangi et al. (2022) indicates that the area has one of the highest November–January recurrence rates of lightning associated with convective storms in South America. Climate change models project a 10–30% increase in precipitation in the region (Barros et al. 2014; IPCC 2021), particularly in summer associated with an increase in convective storms. These climate projections suggest possible increases in fire occurrence and extension due to (1) an increase in weather conditions favorable for fire spread (heat and lack of rainfall); (2) an increase in fuel availability; and (3) a larger number of lightning ignitions. Therefore, we would expect a greater occurrence of fires associated with warmer and drier periods leading to greater flammability of fuels accumulated during previous relatively wet periods. Considering that the type of fuel and its availability influence fire recurrence, differences in vegetation associated with spatial environmental heterogeneity will also lead to a different fire recurrence in the landscape at regional scale. This work is the first attempt to characterize the fire regime in *Prosopis* woodlands by reconstructing the spatial and temporal variations of fires and establishing their relationships with climatic variability in the Central Monte, Argentina.

Methods

Study area

The study area is located in the Monte biogeographical province, specifically between the main watercourses of the Diamante and Atuel rivers, in the southern sector of the Central Monte, and covers 27.3 million hectares (Fig. 1) (Rundel et al. 2007). The climate is semi-arid, with a mean annual temperature of 15.4 °C, total annual precipitation of 400 mm, and prevailing winds from the S-SE (General Alvear weather station located at 35° S, 67° 39' W, 465 m a.s.l.; Gonzalez Loyarte et al. 2009). Summer rains are associated with convective thunderstorms with high electrical activity and hail, although most of the year experiences a pronounced water deficit. The vegetation consists of a mosaic of various types of communities: the forests, dominates by *Prosopis flexuosa* and *Geoffroea decorticans*; the shrublands, dominated by *Larrea divaricata, L. cuneifolia, Condalia microphylla* and *Atriplex lampa*; and the psammophilous grassland, dominated by *Elionurus muticus* and *Hyalis argentea* (Tacchini et al. 2014). The recurrent fires caused changes in the structure, shape, and community composition, and controlled the transitions among vegetation types. In addition, fires cause *Prosopis flexuosa* trees to show

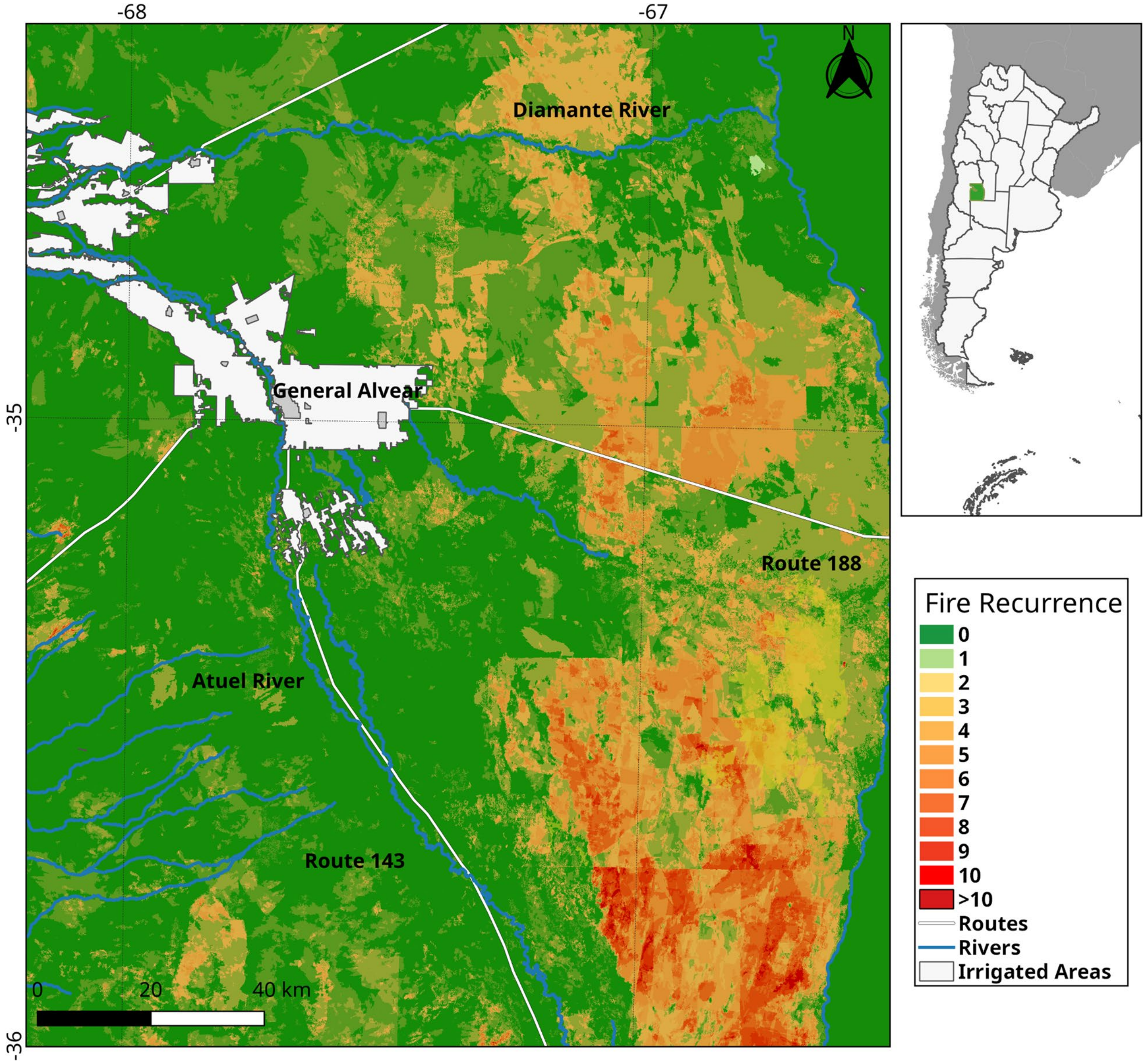

Fig. 1 Fire recurrence during the study period. The green area on the map of Argentina represents the study area. The different colors represent the number of fires between the seasons 1985–1986 and 2022–2023

numerous smaller stems. Therefore, fire recurrence can induce positive feedback that generates new stable states, commonly dominated by shrubs or grasses (Cesca et al. 2014). Extensive cattle ranching is practiced in the area for the commercial sale of their meat. This contrasts with other woodlands in the region that follow a subsistence economic model (Guevara et al. 1993, 2009).

Reconstruction of fire history and spatial distribution of burnt areas

We reconstructed the fire history of the area from 1984 to 2023. In the area, the growing season starts in October and ends in April–May, and fires occur between August and February, with the largest concentration in the spring months (Fischer et al. 2012). Therefore, the multi-temporal reconstruction of fires in the area was conducted by separating events that occurred between July and June of the following year (hereafter fire season).

To determine the surface area affected by the fire season, we used satellite imagery from the 1985–1986 through 2022–2023 fire seasons. Imagery processing was performed using Google Earth Engine. This cloud-based platform allows access and processing of widespread spatial resources and satellite image collections, and to run supervised classifications for fire detection (Gorelick et al. 2017). We used the Landsat Simple Composite algorithm to obtain each mosaic, a combination of the best available scenes from Landsat 5-TM, Landsat 7-ETM+, and Landsat 8-OLI-TIRS sensors (30 m spatial resolution) in terms of cloud cover and reflectance. For each fire season, two mosaics were assembled, and the scenes obtained between August and September and January and March were compared, taking into account the fire season. To detect fire in each mosaic, a combination of false composite color bands was first used, which facilitated the identification of burned areas by shape, texture, and hue (Roy and Boschetti 2009; Levin and Heimowitz 2012; Chen et al. 2022). In this way, it was possible to visually identify burnt areas for each season.

Before performing the classifications, we applied a mask to exclude confusing areas, such as the productive irrigated oases. Then, supervised classifications (Random Forest Algorithm) were applied, techniques previously used in other regions of the world to identify burned areas and to map dryland forests (Chuvieco et al. 2019; Manzo-Delgado and Lopez-Garcia 2020; Guida-Johnson et al. 2021). We chose the Random Forest algorithm to perform the classifications because of its effectiveness, predictive power, and accuracy (Breinman 2001). This technique has been used to map tree cover and carbon stocks in ecologically related landscapes such as the Espinal (González-Roglich and Swenson 2016).

For supervised classifications, each mosaic was classified with training samples based on regions of interest, which provide a representative description of the total population, defining different spectral classes. The size recommended for one region of interest is linked to the characteristics of the technique used for the classification and the type of object classified (Foody and Mathur 2004). Training samples were set for the types of burnt and unburnt areas and distributed throughout the image to collect homogeneous samples without ignoring the natural variability of the system (Foody and Mathur 2004). The regions of interest were redefined in each image, excluding routes, firewalls, rivers, and cattle trails, to avoid erroneous results in the final product of the classifications.

The classification results were corroborated with the fire reports and blueprints available from the Department of Renewable Natural Resources (DRNR) of the Government of Mendoza. The fire reports are spreadsheets filled out by firefighters of the Provincial Plan for Fire Management, where the areas affected by fire are registered using GPS. The fire blueprints are prepared by the firefighters using an expedited methodology that consists of walking through the areas affected by the fire and delineating the affected area on a map. Validation points based on high-resolution imagery available in Google Earth were used to create error matrices for each classification. We tested 25 fire seasons using this method and found an average accuracy of 83.80% (Additional file 1: Table S1). For these fire seasons, we calculated overall accuracy, producer and user accuracy for fire class, and quantity and assignment disagreement (Congalton 1991; Pontius and Millions 2011; Warrens 2015). Overall accuracy is the most precise descriptive statistic, representing the proportion of correctly classified pixels (Congalton 1991). Producer accuracy indicates the probability that a reference pixel is correctly classified, while user accuracy estimates the probability that the pixel on the map represents that class on the ground (Congalton 1991). The disagreement measure is an overall accuracy complement that can be decomposed into quantity and allocation disagreement (Warrens 2015).

Finally, we observed that the total area burned for the 1985–1986, 1986–1987, and 1987–1988 seasons was consistent between Loggio (1992) and our satellite-derived data. Then, we added the area burned in the 1984–1985 season obtained by Loggio (1992) to the fire record, but this data was not included in the statistical analysis.

A 39-year burned area record was developed from the available information. We then created maps of areas with different post-fire recovery periods, grouping fires into 5-year periods, and fire recurrence (number of fires during the period) using map algebra. Once the database was organized and the burned area for each season was generated in a raster format, the map algebra was applied using the tools available in GIS. In this way, the raster combination of each year in successive layers allowed us to identify the fire episodes that occurred during the study period, the unburned areas, and the recurrence of fires in the entire area (Collado and Echeverría 2005). In order to identify dominant cycles of fire recurrence, the burned area record for the period 1984–2023 was analyzed using Blackman–Tukey spectral analysis (Jenkins and Watts 1968).

Relationships between fire and climate

Climate data were collected from various stations in the vicinity of the study area. For precipitation, records from the following stations were used: San Rafael Airport, Río Atuel, Ñacuñán (all in Mendoza Province), and Santa Rosa (in La Pampa Province). Except for Rio Atuel, where data were not available, the same station records were used for temperature. For each individual record to have the same weight in the regional record, we normalized the temperature series to the 1975–2023 period common to all stations. The deviations of the data of each series were determined with respect to the mean of the common period (1975–2023), and this value was divided by the standard deviation of the series in the common period. Finally, we obtained the regional record by averaging the normalized deviations of the data from all four-station series. For precipitation, we obtained the percentages of precipitation relative to the average precipitation during the same common period for each period analyzed (year, season, or month). The regional mean was obtained by averaging the values from all five stations.

Relationships between annual burnt area and regional variations in precipitation and temperature were determined using correlation matrices during the same common period 1984–2023. Prior to analysis, the burnt area data were log-transformed and the normality of the variables was analyzed. Since some of the series showed non-normal distributions, relationships were determined using Spearman correlations, which provide more robust relationships for non-normal distributions (Zar 1984). After identifying the monthly climate data most strongly related to fire occurrence, we grouped them into seasonal averages.

We used Superposed Epoch Analysis (SEA) to assess the influence of climatic conditions in previous years and the year of fire occurrence (Swetnam 1993). The six fire seasons with the largest (1986–1987, 1993–1994, 2000–2001, 2003–2004, 2013–2014, 2017–2018) and smallest (1991–1992, 1996–1997, 2004–2005, 2011–2012, 2014–2015, 2015–2016) burned areas were selected for analysis. Seasonal (November–December) precipitation and (January–February) temperature records in a 6-year window, starting 3 years before and ending 2 years after the fires, were considered in the SEA analysis. Although climate conditions in years $t+1$ and $t+2$ do not influence fires in year t, their inclusion can help to detect climate conditions following fire years (Grissino-Mayer 2001). The deviations for each of the 6-year windows (one per fire event) were superimposed and averaged to obtain the climatic patterns associated with the largest and smallest burned areas. Monte Carlo simulation techniques were used to evaluate the statistical significance of the resulting climatic patterns. 1000 simulations based on random sampling with replacement were performed to determine the probability of occurrence associated with the mean deviations of the resulting precipitation and temperature patterns (Mooney and Duval 1993). The EVENT program (version 6.02P) was used to perform the SEA (http://www.ltrr.arizona.edu/software.html). In both analyses, significant differences were estimated at $p < 0.05$.

Finally, using the facilities provided by Climate Explorer (https://climexp.knmi.nl/start.cgi), we determined the ERA5 spatial patterns of precipitation and temperature anomalies over South America south of 10° S associated with the six seasons with the largest (1986–1987, 1993–1994, 2000–2001, 2003–2004, 2013–2014, 2017–2018) and smallest (1991–1992, 1996–1997, 2004–2005, 2011–2012, 2014–2015, 2015–2016) burned areas. Initially, climate anomalies were calculated for the entire 1984–2023 study period. However, because four of the six largest burned areas occurred in the first 20 years of our record, anomalies were also calculated for the periods 1984–2003 and 2004–2023. This allowed us to assess whether the relationships between climate variability and fire occurrence were stable over time.

Results

Fire history

A large part (1,489,209 ha) of the analyzed area (2,729,797 ha) suffered at least one fire in the last 39 years. Considering that there are areas with high fire recurrence, the total area burned in the entire period 1985–2023 is 3,133,883 ha (Fig. 1). The areas with the highest fire recurrence were found in the central and southeastern sectors, with more than 10 fire events between 1985 and 2023. The highest percentage of unburned area was found in the southwest and northeast sectors (Fig. 1). As a result, the region is a mosaic of areas with different fire recurrences (Fig. 1) and post-fire recovery times (Fig. 2).

The areas affected by fire showed a high interannual variability, with seasons without fires or exceeding 450,000 ha burnt. Within the period analyzed, 6 seasons were distinguished with fire events larger than

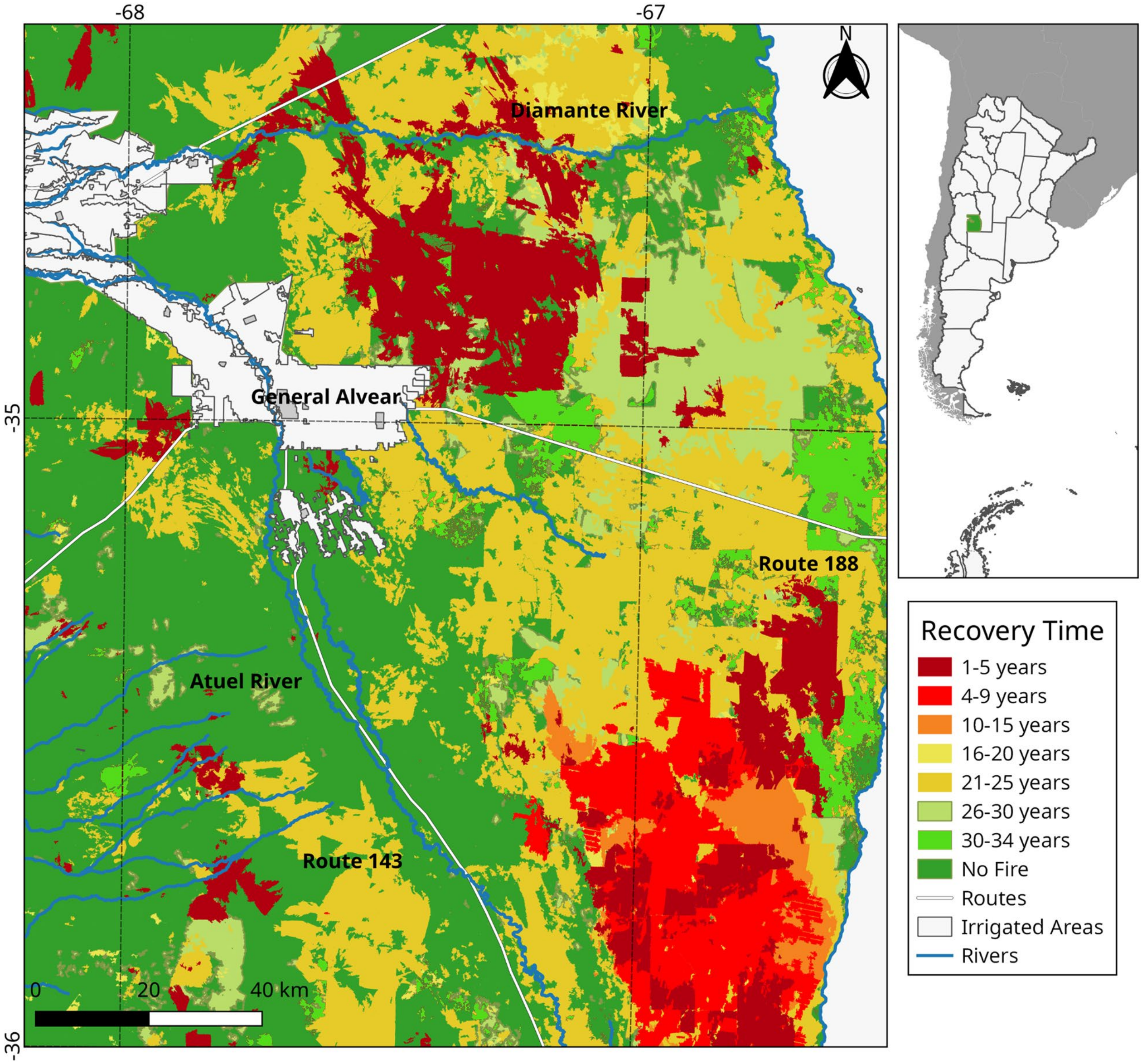

Fig. 2 Areas with different post-fire recovery times in southeastern Mendoza. The green zone in the location map represents the study area. The different colors represent the recovery time in years since the last fire

140,000 ha: 1986–1987, 1993–1994, 2000–2001, 2003–2004, 2013–2014 and 2017–2018. There were no two consecutive years with large fire events (Fig. 3).

Relationships between fire and climate

Relationships between interannual variation in total burned area and climatic factors showed that fire extent was inversely related to total precipitation during the current growing season and positively related to precipitation during the previous growing season (Figs. 3, 4). In contrast, the burned area was positively related to temperature during the growing season and inversely related to temperature during the previous year (Figs. 3, 4). The strongest relationship between burnt area and precipitation during the period 1984–2023 was observed for the period November–December during the season of the fire events ($r = -0.52$, $p < 0.05$; Table 1). The strongest relationship between burnt area and precipitation during the season preceding the fire occurred when considering the late winter–spring period (August–October, $r = 0.54$; $p = 0.001$; Table 1). Temperatures during the current summer were positively correlated with total burnt area, reaching statistical significance in February ($r = 0.39$; $p = 0.02$) (Fig. 4). The mean temperature of the period

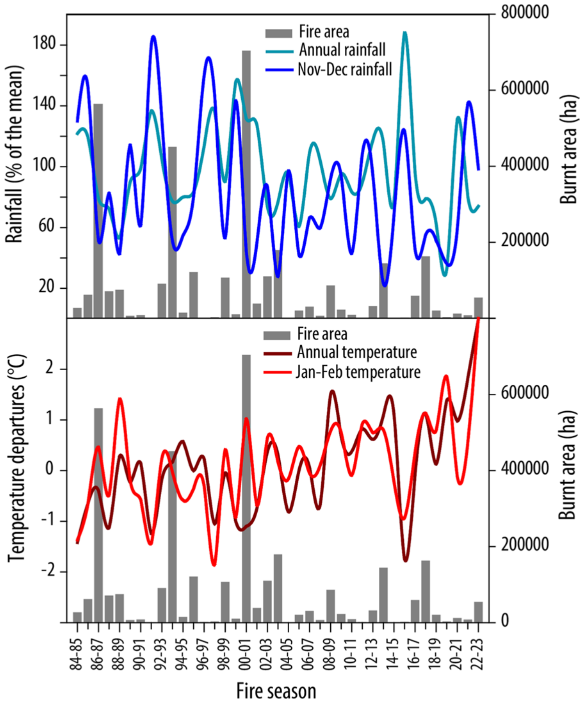

Fig. 3 Burnt surface area and the regional climate of southeastern Mendoza for the 1984 to 2023 period. Relationship between annual and the November–December rainfall (top), measured as a percentage of the mean for that period. Relationship between the surface burnt area and the deviation of the mean annual and January–February temperature (bottom)

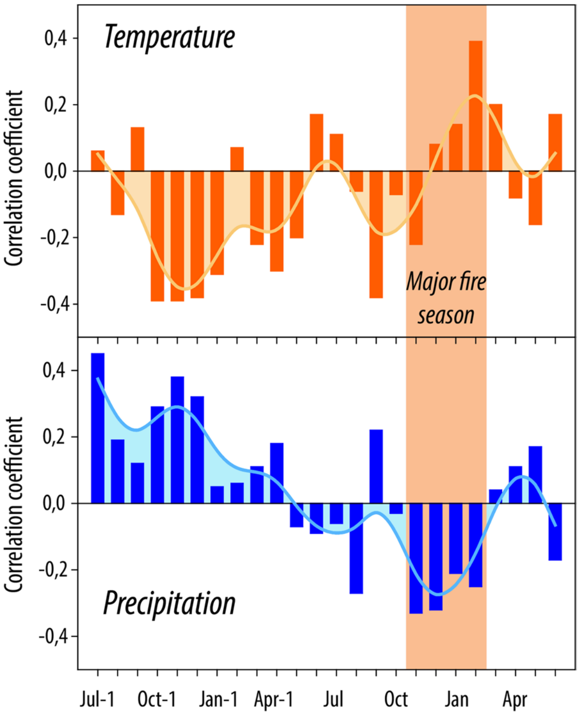

Fig. 4 Variations of the Spearman correlation coefficient between burned area and monthly mean temperature (top) and between area burned and anomalies in monthly total precipitation (bottom) from July of the previous year to June of the current year. To facilitate visualization, the relationships are also shown in smoothed form using a 6-month spline filter interval

January–February was the most strongly correlated with the burnt area (Table 1). The years with the largest burnt area showed higher than average temperatures in January–February (Fig. 3). In contrast, spring temperatures were not correlated with burned area. Temperatures during the previous year were negatively correlated with total burned area (Fig. 4; Table 1).

Spectral analysis showed that both November–December precipitation and burned area showed a very pronounced 6–7 year cycle (Fig. 5). We observed that the six seasons with the most extensive fires coincided with November–December precipitation 60% below the mean. However, not all seasons with precipitation 60% below the November–December mean resulted in fire occurrence (Fig. 3). In fact, similar conditions were recorded in other seasons (e.g., 1988–1989, 2001–2002, 2005–2006, 2010–2011, 2019–2020). Similarly, not all years with abundant rainfall and low temperatures lead to large fires in the following year.

Superposed Epoch Analysis (SEA) showed that the years with the largest area burned were associated with above average precipitation in the previous growing season, but higher temperatures and significantly lower precipitation in the year of the fire. The years with the fewest hectares burned showed a pattern consistent with high precipitation and low temperatures in the year of fire (Fig. 6).

The spatial patterns of precipitation and temperature anomalies associated with the six years with the largest and smallest areas burned during the period 1984–2023 showed that fire seasons were associated with November–December precipitation deficits along a territorial band over Argentina, extending from the Andean Piedmont at 35°S to the Atlantic coast at 39°S (Fig. 7a). The years with largest burned areas showed positive but weaker temperature anomalies in January and February over the same territory (not shown). Over the study area, negative November–December precipitation anomalies associated with large fires range from 12 to 24 mm with respect to the average (Fig. 7a). In contrast, positive November–December precipitation anomalies between 6 and 12 mm were recorded during the seasons with smallest burned areas (Fig. 7b). A similar analysis, considering separately the periods 1984–2003 and 2004–2023, clearly showed that the spatial patterns of November–December precipitation anomalies were comparatively different between the two intervals. During the earlier period,

Table 1 Correlations between burnt area and the sum of precipitations by periods, and between burnt area and the mean temperature by period

	Period	Precipitation		Temperature	
		r	*p*	*r*	*p*
Fire season	Jul–Jun	− 0.25	0.14	0.09	0.59
	Jul–Dec	**− 0.34**	**0.04**	− 0.03	0.84
	Jan–Jun	− 0.05	0.76	0.23	0.17
	Nov–Dec	**− 0.49**	**0.003**	–	–
	Oct–Dec	**− 0.40**	**0.01**	–	–
	Sep–Nov	–	–	− 0.25	0.14
	Dec–Feb			**0.40**	**0.01**
	Jan–Feb			**0.42**	**0.01**
	Jan–Mar			**0.41**	**0.01**
Season previous to fire	Jul–Jun	0.30	0.07	**− 0.40**	**0.01**
	Jul–Dec	**0.54**	**0.001**	**− 0.37**	**0.02**
	Jan–Jun	− 0.001	0.99	**− 0.32**	**0.05**
	Oct–Dec	**− 0.40**	**0.01**	–	–
	Nov–Dec	**− 0.49**	**0.003**	–	–
	Nov–Jan	**− 0.50**	**0.002**	–	–
	Jan–Feb	–	–	− 0.20	0.22
	Dec–Feb	–	–	− 0.26	0,11
	Jan–Mar	–	–	− 0.19	0.25

The correlations in bold are significant by $p < 0.05$. r = correlation coefficient and p = significance value. N = 39. Empty cells indicate no data

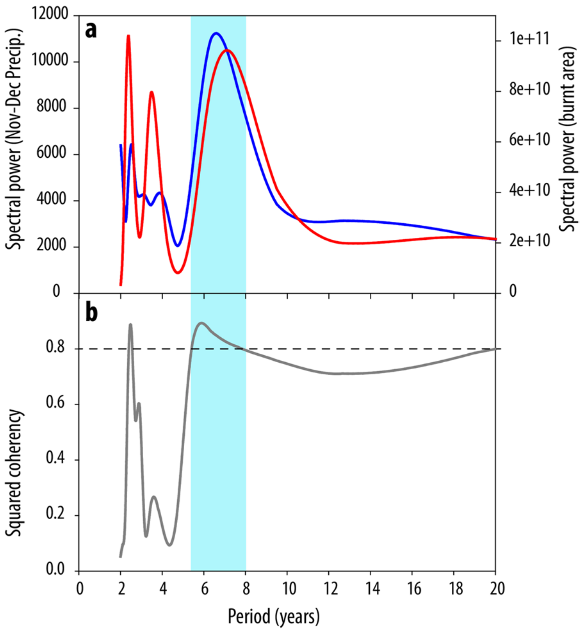

Fig. 5 Blackman–Tukey (BTM) power spectra of interannual variations in burnt area and Nov–Dec precipitation in the study area estimated over the interval 1984–2023 (**a**). The coherency spectrum between these two records is shown in **b**. Records are highly coherent at 6–8-year wavelengths (light blue box)

precipitation deficits associated with years of extensive fire (> 140,000 ha) were much more pronounced over the study area, with precipitation reductions of more than 30 mm (Fig. 7c). In contrast, spatial precipitation deficits in the more recent period were very small or absent in the study area (Fig. 7d). The analysis of the regional precipitation series showed that during the period 1984–2003, the November–December precipitation was more abundant (110% of the mean), but also much more variable (SD 57%). In contrast, during the period 2004–2023, precipitation was much lower (88% of the mean) and less variable between years (38%, Fig. 7e).

Discussion

Fire history

The interannual variability in the extent of fires in the southern sector of Central Monte is large, with almost no fires in some years and exceeding 600,000 ha burned in others. In the last four decades, half of the total area of more than 2,700,000 ha has burned at least once, including sectors that have experienced up to 14 fires during this period. Collado and Echeverría (2005) and Fischer et al. (2012), using a combination of remote sensing and GIS techniques to assess fire variability, suggest that ecosystem dynamics in semi-arid regions of Argentina are strongly controlled by fire, as has been observed in various forests around the world (Turner et al. 2011; Pricope and Binford 2012; Ibarra-Montoya and Huerta-Martinez 2016; Manzo-Delgado and Lopez-Garcia 2020).

The existence of highly coherent common oscillations between interannual variations in burned areas and November–December precipitation (Fig. 5) suggest that regional climate variability is an important driver of fire in Central Monte, as has been documented by numerous authors for different ecosystems around the world (Veblen et al. 1999; Zhang et al. 2010; Turner et al. 2011; Ibarra-Montoya and Huerta-Martínez 2016; Manzo-Delgado and López-García 2020). However, spatial heterogeneity in the distribution and recurrence of fires did not appear to be random, as would be expected when climate is the only factor regulating fire probability. This was demonstrated by the frequent occurrence of fires in certain areas and the lack of fires in others (Figs. 1, 2). This suggests that other variables, including physical (i.e., topography), biological (i.e., vegetation type), and/or anthropogenic (i.e., land use) factors simultaneously influence fire regimes (Whelan 1995; Fischer et al. 2012; Archibald et al. 2018). For example, the area with the highest fire return is largely dominated by grasses, with scattered emergent woody plants (*Prosopis flexuosa, Geoffroea decorticans, Larrea* spp.) at low densities (Villagra et al. 2009; Tacchini et al. 2014). Grasslands seem to favor the occurrence and spread of fires, as has been

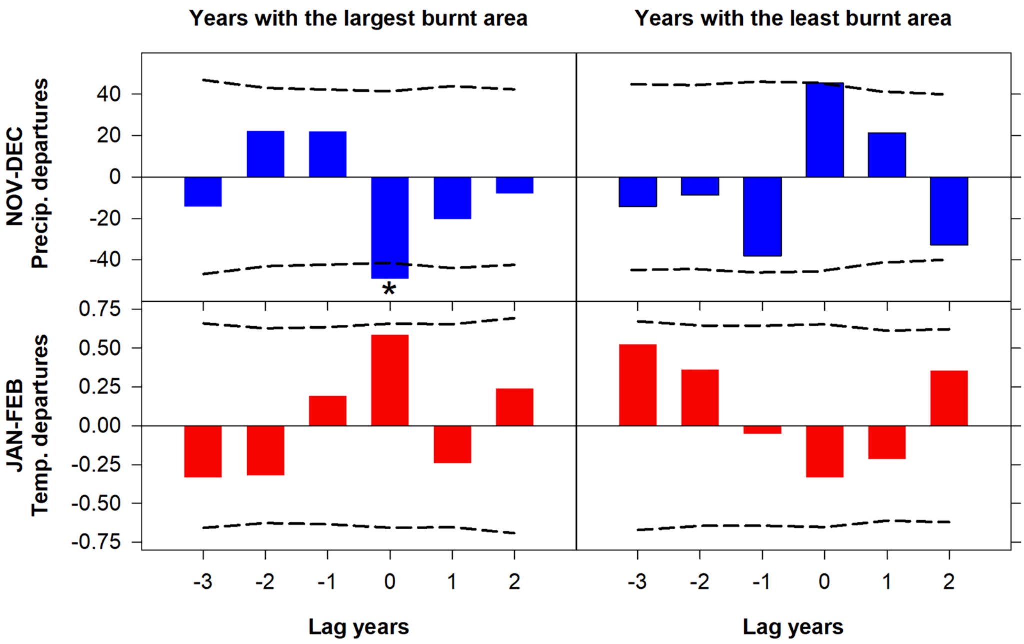

Fig. 6 Regional January–February temperature anomalies (in °C) and November–December precipitation anomalies (in percent of mean) for 3 years before and 2 years after the fire (year 0). Deviations on the left correspond to the 6 years with the largest area burned, while those on the right correspond to the 6 years with the smallest area burned in the interval 1984–2023. The bars with asterisks indicate significant differences ($p < 0.05$) from the means obtained in 1000 Monte Carlo simulations based on the same number of years as the events (Mooney and Duval 1993). The dashed lines correspond to the 95% confidence interval

observed in other semi-arid regions (Verhoeven et al. 2020). An interesting aspect to be analyzed in future research is the existence of possible positive feedbacks between fire and vegetation that may contribute to the maintenance of grasses in a relatively stable stage, as has been observed in Monte Austral (Rostagno et al. 2006). In this sense, high fire recurrence modifies the density and growth morphology of *Prosopis flexuosa* (the dominant tree species in the area), creating a landscape dominated by shorter individuals with numerous smaller stems, a loss of diametric classes > 20 cm basal diameter, concurrent with an increase in the grass layer (Cesca 2013; Cesca et al. 2014). Could this change in community structure favor fire recurrence by creating positive feedback between vegetation and fire?

Our study showed that the spatial variability of fire creates a mosaic of patches with different post-fire recovery times and fire recurrences. This fire-induced heterogeneity could increase diversity at the regional scale, affecting forest and livestock productivity in the area (Scholes and Walker 1993; Huston 1998; Zinck et al. 2010; Cesca et al. 2014; Burkle et al. 2015). However, the positive effect of fire on landscape diversity appears to be associated with fires of low severity and small size (Zinck et al. 2010; Miller and Safford 2020), while landscape diversity decreases in areas with high severity or recurrent extended fires (Mahood and Balch 2019; Zinck et al. 2010; Moghli et al. 2022). In contrast, the effect of fire on local diversity is variable and cannot be clearly established at smaller spatial scales (Giorgis et al. 2021). However, frequent and severe fires have been observed to reduce alpha diversity, particularly of woody species (Mahood and Balch 2019). Besides, fire recurrence has been observed to reduce many ecosystem services and ecosystem multifunctionality, effects that can be buffered in areas with long post-fire recovery times (Moghli et al. 2022). Future research should investigate the causes of the irregular shape and size of fires. In this sense, firefighting techniques developed by the Provincial Fire Management Plan are likely to influence the duration and size of fires because, as observed in many cases, firebreaks stop fire spread (personal communication from Mendoza firefighters). This suggests that fire management tasks could modify the spatial heterogeneity of the landscape. Thus, the evaluation of the relationships between the size, severity and frequency of fire events in the study area could help to model the spatial heterogeneity generated by fires on vegetation structure and diversity, useful information for management strategies in a region where the main economic activities are supported by grass and forest productivity.

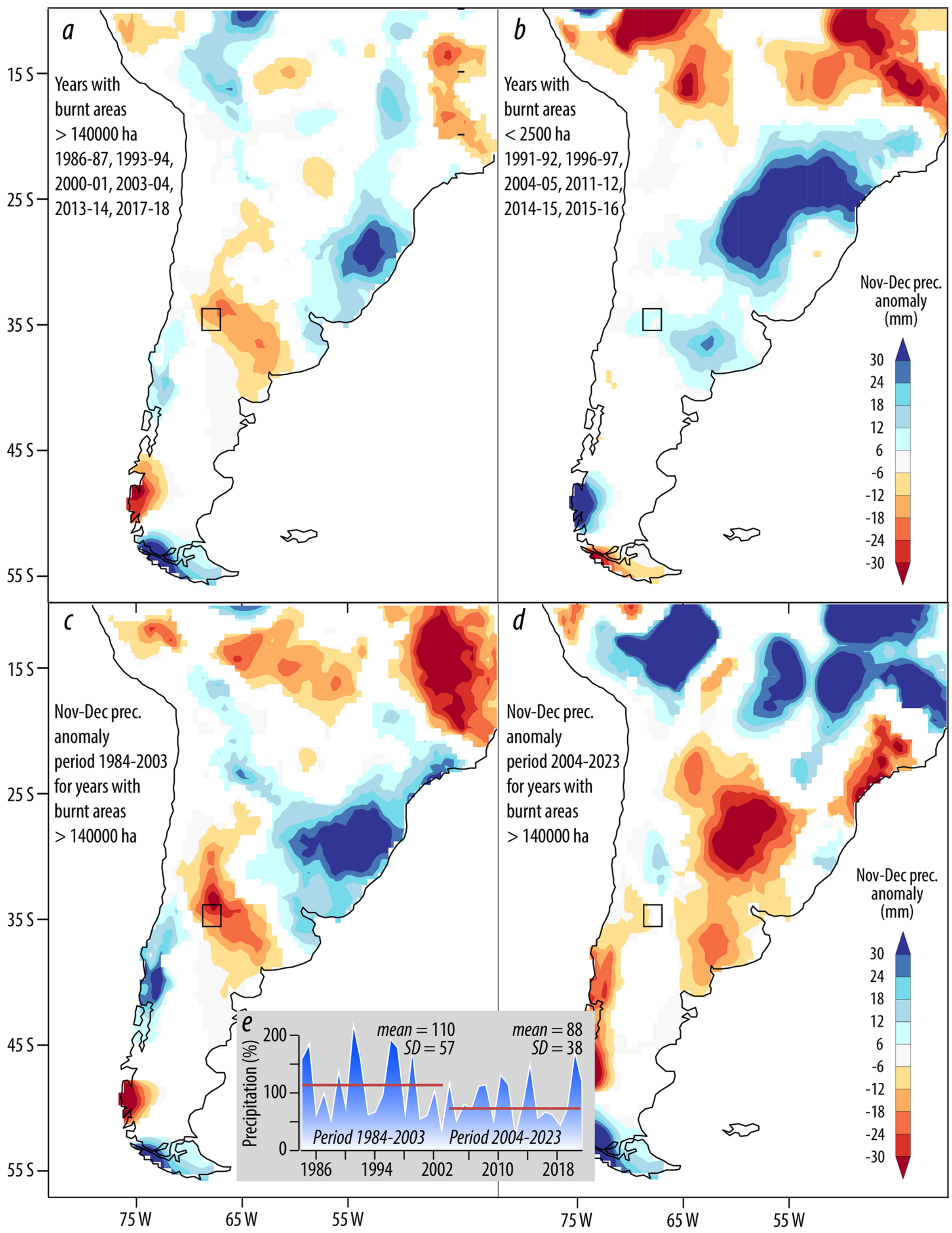

Fig. 7 Spatial association of November–December precipitation anomalies with: **a** the six years with largest burned areas during the period 1984–2023; **b** the 6 years with the smallest burned areas during the same period; **c** the years with the largest (> 140,000 ha) burned areas for the period 1984–2003; and **d** the years with the largest burned areas for the period 2004–2023. The black square represents the study area. Inset (**e**): precipitation anomalies (percentage of the long-term mean) for both periods. Standard deviations (SD) are also shown for both periods

Relationships between fire and climate

The three approaches used here supported a strong relationship between the occurrence of extensive fires and climate in southeastern Mendoza. At seasonal scale, fires were largely favored by the combination of abundant spring–early summer precipitation in the previous growing season, followed by below-average spring–early summer precipitation in the current fire year. We propose that wet spring–early summer in the previous year would favor the accumulation of fuels that increase their flammability during the subsequent dry-hot growing season. This coordinated process should be critical in arid environments where biomass production is lower in most years. Our results supported previously documented climate-fire relationships in arid to semi-arid regions, suggesting that the occurrence of large fires depends on the accumulation of fuels such as desiccated grasses, which are more susceptible to fire in dry years (Swetnam and Betancourt 1998; Brooks and Matchett 2006; Pausas and Bradstock 2007; Pricope and Binford 2012; Verhoeven et al. 2020). Fischer et al. (2012, 2015) noted that the highest density of fires in the central semi-arid region of Argentina overlaps with our study area. These authors found that fires are concentrated during the winter–spring transition, when water deficit peaks due to the increase in temperature after winter and the delay in summer rains. Verhoeven et al. (2020) also highlighted the importance of pre-fire year rainfall in Australia's drylands. However, they emphasized the importance of rainfall two years before the fire, while area burned was negatively related to rainfall in the previous year. In contrast, Turner et al. (2008) reported that burned area in semi-arid northern Australia was related to rainfall in the previous year. The semi-arid climatic regimes in both southeastern Mendoza and northern Australia may explain the consistency of our results with those of Turner et al. (2008). In semi-arid environments, a rainy season may provide sufficient water inputs for abundant fuel production, whereas in arid areas, biomass accumulation may require more time. The degree of water deficit and the duration of the dry season are essential factors that determine the amount and state of fuel available for ignition. Llorens and Frank (2003) also document large fires in *Prosopis caldenia* forests at the end of the 1990s associated with more abundant precipitation, which in turn increased the amount of small fuel production.

At the interannual scale, spectral analysis revealed the presence of pronounced 6–7 year oscillations in regional November–December precipitation over the last 40 years. These cycles were highly coherent with the occurrence of extensive fires in southeastern Mendoza every 6–7 years (Fig. 5), suggesting that variations in precipitation during the fire season are the main driver of interannual variations in total burned area. However, the spatial relationships between climatic conditions and fires do not appear to be stable over time. For example, the spatial relationships between November–December precipitation and fires > 140,000 ha were stronger and more geographically extensive during the period 1984–2003 (Fig. 7). Interestingly, 4 of the 6 largest fires recorded since 1984 occurred during this period. During this time interval, precipitation was 30% higher than in the more recent 2004–2023 period (Fig. 7e), allowing for greater fuel production and accumulation. Similarly, November–December precipitation was 1.5 SD more variable in the 1984–2003 period than in the 2004–2023 period (Fig. 7e), favoring not only greater fuel production in years of abundant precipitation, but also intensifying fuel drying during dry-hot fire seasons. Our results suggest that fire occurrence in the Monte is not only dependent on dry conditions during fire seasons but is also exacerbated by greater interannual variability in precipitation. Periods with higher interannual variability would favor not only the production of fuel in relatively wet years, but also strong desiccation in dry years, inducing the ignition and spread of fires.

According to the national fire management plan, the proportions of fires started by natural (lighting) and human (including unintentional and deliberate) ignition sources were similar in proportions during the period 2000 and 2010 in the study area (Cesca 2013). In any case, ignition sources seem to be abundant across the region (Rasmussen et al. 2014; DiGangi et al. 2022) and should play a minor role as control factors of the temporal variability of fire occurrence. Defossé and Urretavizcaya (2003) pointed out that once ignited, the evolution of the fire depends on the quantity and characteristics (flammability, size) of the fuel, relative humidity, temperature, wind, slope, and exposure. Fischer et al. (2015) observed that fire duration and extent depend on biomass regulation, mainly in shrublands and agricultural lands, whereas wildfires largely depend on fuel conditions and the presence of degraded forests (i.e., grasslands). More research is needed to understand the complex interactions between climate, fuel availability and fire events. Our results contribute to understanding the role of weather factors but an integrated analysis of the complex interactions among climate, fuel, and other involved factors is recommended for planning and management in semi-arid areas, since fires usually occur on a regional scale, with ecological consequences that transcend jurisdictional boundaries (Avitabile et al. 2013).

One of the factors that could be important in controlling fire occurrence is the previous occurrence of large fires (e.g., 1986–1987, 1993–1994, 2000–2001 and 2017–2018) and this could explain the 6–7 year cycle of burnt area observed in the spectral analysis. In these cases, fire consumes most of the fuel and two to seven growth seasons are needed to recover the fuel declining the probability of occurrence and the distance of fire spread. In example, after a large fire (1986–1987), at least two humid seasons (e.g., 1988–1989, 1990–1991) would be necessary to create the amount of fuel for the next event (e.g., 1993–1994). Therefore, our results supported the idea that large fire events suppress the probability of fire occurrence in the coming years. Further research is needed to understand the mutual regulation between fuel availability and fire events.

Climate change models project an increase in the occurrence of fire weather conditions under both moderate and high levels of global warming, future scenarios that are of great concern to society (IPCC 2021). However, some authors suggested that the global trend in burned area is decreasing or not increasing significantly, as the effects of warmer temperatures and drought are offset by increased humidity, population growth, and changes in land use (Doerr and Santin 2016; Arora and Melton 2018; Forkel et al. 2019). Thus, the global trend is the result of the balance of compensating trends of controls occurring at the regional scale. Our results were consistent with climatic conditions being one of the main drivers of fire occurrence in the Central Monte, southeast of Mendoza. Interannual climatic variability appears to be the main factor associated with large fire events. Model simulations for the twenty-first century predict an increase in the amount and temporal variability of precipitation, warmer temperatures, and a high frequency of thunderstorms for the Central Monte (Labraga and Villalba 2009). The increase in precipitation may lead to an increase in biomass production, which, combined with more frequent drought events, will increase fuel availability, a limited fire resource in arid lands (Forkel et al. 2019). The highest frequency of fires in Central Monte occurs in areas with total annual precipitation between 200 and 400 mm, where wet and dry years frequently alternate (Villagra et al. 2009). In addition, the increase in the number of electrical storms would increase the number of ignition sources, although this factor is not important for the expansion of fires in the study area. In addition, human activities also affect the extent and shape of burned areas through firefighting techniques, the influence of roads, and land-use changes. The diversity of factors influencing fire suggests that future changes in fire dynamics are complex and not straightforward.

The knowledge provided by our study is important for developing guidelines for fire decision-makers in the southeastern forests of Mendoza. Particular attention should be paid to wet years followed by dry years. In this sense, preventive and contingency resources should be ready, focusing on firewall maintenance and personal availability.

Conclusions

Most of the study area in the southern Central Monte has been affected by at least one wildfire in the last 39 years. The distribution of fires is spatially heterogeneous and temporally variable, resulting in a mosaic of patches with different recurrence and recovery times. The spatial heterogeneity is related to vegetation patterns and land use. The temporal variability of fires is strongly influenced by climate variability, since fires are favored by the combination of abundant spring–early summer precipitation in the previous growing season, followed by below-average spring–early summer precipitation in the current fire year. These conditions could increase fuel production and result in subsequent drying. Consequently, the largest fires are concentrated in periods of high interannual precipitation variability. Climate change scenarios indicate an increase in temperature, precipitation variability, and storm occurrence in the region, suggesting future changes in fire dynamics induced by increased fuel production and more frequent electrical storms. Our results contribute to the development of fire guidelines to decision-makers in southeastern Mendoza forests, focusing on periods of wet years followed by dry years that favor fire occurrence and spread.

Abbreviations

GIS	Geographical Information System
GPS	Global Positioning System
SEA	Superposed Epoch Analysis
SD	Standard deviation

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13717-023-00481-6.

Additional file 1: Table S1. Accuracy indexes from error matrixes based on high-resolution images available from Google Earth.

Acknowledgements

We thank Gualberto Zalazar, Anahí Miner, Alberto Ripalta, Carlos Cesca, Sergio Londero, Alberto Ripalta, Agustina Aranda and Hugo Debandi for their collaboration at different stages of the project. We thank Anabela Bonada, for improving the English version of the manuscript. We thank to the Department of Renewable Natural Resources (DRNR) of the Government of Mendoza and the Provincial Plan for Fire Management for providing us with the fire blueprints and collaborating in the corroboration of the first fire maps.

Author contributions

PEV and EC developed the ideas for this manuscript, contributed to the design, to the analysis and interpretation of data, to draft and revise the manuscript. EC, LMA and SD conducted the remote sensing and geographic information systems analysis. RV contributed to the analysis and interpretation of data and to revise the manuscript. All authors contributed to the writing of the manuscript. All authors read and approved the final manuscript.

Funding

This research was supported by Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Universidad Nacional de Cuyo, Ministerio de Ciencia, Tecnología e Innovación, Argentina (PITES 03 and Red Bosque-Clima contribution No. 1).

Availability of data and materials

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

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Received: 29 September 2023 Accepted: 26 December 2023

References

Archibald S, Lehmann CER, Belcher CM, Bond WJ, Bradstock RA, Daniau A-L, Dexter KG, Forrestel EJ, Greve M, He T, Higgins SI, Hoffmann W, Lamont BB, McGlinn DJ, Moncrieff GR, Osborne CP, Pausa JG, Van der Werf GR, Zanne AE (2018) Biological and geophysical feedbacks with fire in the Earth system. Environ Res Lett 13(3):033003. https://doi.org/10.1088/1748-9326/aa9ead

Arora VK, Melton JR (2018) Reduction in global area burned and wildfire emissions since 1930s enhances carbon uptake by land. Nat Commun 9:1326. https://doi.org/10.1038/s41467-018-03838-0

Avitabile SC, Callister KE, Kelly LT, Haslema A, Fraser L, Nimmob DG, Watsonb SJ, Kenny SA, Taylor RS, Spence-Bailey LM, Bennett AF, Clarke MF (2013) Systematic fire mapping is critical for fire ecology, planning and management: a case study in the semi-arid Murray Mallee, south-eastern Australia. Land Urban Plan 117:81–91. https://doi.org/10.1016/j.landurbplan.2013.04.017

Barros VR, Boninsegna JA, Camilloni IA, Chidiak M, Magrín GO, Rusticucci M (2015) Climate change in Argentina: trends, projections, impacts and adaptation. Wiley Inter Rev Clim Change 6(2):151–169. https://doi.org/10.1002/wcc.316

Breiman L (2001) Random forests. Mach Learn 45:5–32

Brooks ML, Matchett JR (2006) Spatial and temporal patterns of wildfires in the Mojave Desert, 1980–2004. J Arid Environ 67:148–164. https://doi.org/10.1016/j.jaridenv.2006.09.027

Burkle LA, Myers JA, Belote RT (2015) Wildfire disturbance and productivity as drivers of plant species diversity across spatial scales. Ecosphere 6(10):202. https://doi.org/10.1890/ES15-00438.1

Cesca EM (2013) Influencia del fuego en la estructura y dinámica de los algarrobales del sudeste de Mendoza. Universidad Nacional de Córdoba, Córdoba, Tesis Doctoral

Cesca EM, Villagra PE, Alvarez JA (2014) From forest to shrubland: structural responses to different fire histories in *Prosopis flexuosa* woodland from the Central Monte (Argentina). J Arid Environ 110:1–7. https://doi.org/10.1016/j.jaridenv.2014.05.025

Chen Y, Hantson S, Andela N, Coffield SR, Graff CA, Morton DC, Ott LE, Foufoula-Georgiou E, Smyth P, Goulden ML, Randerson JT (2022) California wildfire spread derived using VIIRS satellite observations and an object-based tracking system. Sci Data 9:249. https://doi.org/10.1038/s41597-022-01343-0

Chuvieco E, Mouillot F, van der Werf GR, San Miguel J, Tanasse M, Koutsias N, García M, Yebra M, Padilla M, Gitas I, Heil A, Hawbaker TJ, Giglio L (2019) Historical background and current developments for mapping burned area from satellite Earth observation. Remote Sens Environ 225:45–64. https://doi.org/10.1016/j.rse.2019.02.013

Collado AD, Echeverría JC (2005) Variabilidad espacio-temporal de los incendios rurales en las provincias de San Luis y Mendoza. 167th Technical Report INTA. Instituto Nacional Tecnologia Agropecuaria, San Luis, Argentina

Congalton RG (1991) A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ 37:35–46. https://doi.org/10.1016/0034-4257(91)90048-B

Defossé GE, Urretavizcaya MF (2003) Introducción a la Ecología del Fuego. In: Kunst R, Bravo S, Panigatti JL (eds) Fuego en los Ecosistemas Argentinos. Instituto Nacional Tecnologia Agropecuaria, Santiago del Estero, Argentina, pp 17–26

Digangi E, Lapierre J, Stock M, Hoekzema M, Cunha B (2022) Analyzing lightning characteristics in central and southern South America. Elect Pow Sys Res 213:108704. https://doi.org/10.1016/j.epsr.2022.108704

Doerr SH, Santín C (2016) Global trends in wildfire and its impacts: perceptions versus realities in a changing world. Phil Trans R Soc B 371:20150345. https://doi.org/10.1098/rstb.2015.0345

Fischer MA, Di Bella CM, Jobbay EG (2012) Fire patterns in central semiarid Argentina. J Arid Environ 78:161–168. https://doi.org/10.1016/j.jaridenv.2011.11.009

Fischer MA, Di Bella CM, Jobbay EG (2015) Influence of fuel conditions on the occurrence, propagation and duration of wildland fires: a regional approach. J Arid Environ 120:63–71. https://doi.org/10.1016/j.jaridenv.2015.04.007

Flannigan MD, Logan KA, Amiro BD, Skinner WR, Stocks BJ (2005) Future area burned in Canada. Clim Change 72:1–16. https://doi.org/10.1007/s10584-005-5935-y

Foody GM, Mathur A (2004) Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. Remote Sens Environ 93:107–117. https://doi.org/10.1016/j.rse.2004.06.017

Forkel M, Dorigo W, Lasslop G, Chuvieco E, Hantson S, Heil A, Teubner I, Thonicke K, Harrison SP (2019) Recent global and regional trends in burned areas and their compensating environmental controls. Environ Res Commun 1:051005. https://doi.org/10.1088/2515-7620/ab25d2

Giorgis MA, Zeballos SR, Carbone L, Zimmermann H, Von Wehrden H, Aguilar R, Ferreras AE, Tecco PA, Kowaljow E, Barri F, Gurvich DE, Villagra P, Jaureguiberry P (2021) Correction to: a review of fire effects across South American ecosystems: the role of climate and time since fire. Fire Ecol 17:21. https://doi.org/10.1186/s42408-021-00107-2

Gonzalez Loyarte MM, Menenti M, Diblasi AM (2009) Mapa bioclimático para las Travesías de Mendoza (Argentina) basado en la fenología foliar. Rev Fac Agra UNCuyo 1:105–122

González-Roglich M, Swenson JJ (2016) Tree cover and carbon mapping of Argentine savannas: scaling from field to region. Remote Sens Environ 172:139–147. https://doi.org/10.1016/j.rse.2015.11.021

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R (2017) Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens Environ 202:18–27. https://doi.org/10.1016/j.rse.2017.06.031

Grissino-Mayer HD (2001) FHX2-Software for analysing temporal and spatial patterns in fire regimes from tree rings. Tree-Ring Res 57(1):115–124

Guevara JC, Paez JA, Estévez OR (1993) Caracterización económica de los principales sistemas de producción ganadera en el Árido Mendocino. Multequina 2:259–273

Guevara JC, Grünwaldt E, Estevez OR, Bisigato AJ, Blanco LJ, Biurrun FN, Ferrando CA, Chirino CC, Morici EF, Fernández B, Allegretti LI, Passera CB (2009) Range and livestock production in the Monte Desert, Argentina. J Arid Environ 73:228–237. https://doi.org/10.1016/j.jaridenv.2008.02.001

Guida-Johnson B, Villagra PE, Alvarez LM, Rojas F, Alvarez JA (2021) Finding woodlands in drylands: bases for the monitoring of xeric open forests in a cloud computing platform. Remote Sens App Soc Environ 22:100528. https://doi.org/10.1016/j.rsase.2021.100528

He T, Lamont BB, Pausas JG (2019) Fire as a key driver of Earth's biodiversity. Biol Rev 94:1983–2010. https://doi.org/10.1111/brv.12544

Huston MA (ed) (1998) Biological diversity. In: The coexistence of species on changing landscapes. Cambridge University Press, Cambridge

Ibarra-Montoya JL, Huerta-Martínez FM (2016) Modelado espacial de incendios: una herramienta predictiva para el Bosque La Primavera, Jalisco, México. Rev Ambi Agua 11:35–49. https://doi.org/10.4136/ambi-agua.1536

IPCC/Intergovernmental Panel on Climate Change. Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M, Leitzell K, Lonnoy E, Matthews JBR, Maycock TK, Waterfield T, Yelekçi O, Yu R, Zhou B (2021) Climate change 2021. In: The physical science basis. Cambridge University Press, Cambridge, United Kingdom

Jenkins GM, Watts DG (eds) (1968) Spectral analysis and its applications. Holden-Day, San Francisco, United States of America

Korb JE, Fulé PZ, Stoddard MT (2012) Forest restoration in a surface fire-dependent ecosystem: an example from a mixed conifer forest,

southwestern Colorado, USA. For Ecol Manage 269:10–18. https://doi.org/10.1016/j.foreco.2012.01.002
Krawchuk MA, Moritz MA (2011) Constraints on global fire activity vary across a resource gradient. Ecology 92:121–132. https://doi.org/10.1890/09-1843.1
Labraga JC, Villalba R (2009) Climate in the Monte Desert: past trends, present conditions, and future projections. J Arid Environ 73:154–163. https://doi.org/10.1016/j.jaridenv.2008.03.016
Levin A, Heimowitz A (2012) Mapping spatial and temporal patterns of Mediterranean wildfires from MODIS. Remote Sens Environ 126:12–26. https://doi.org/10.1016/j.rse.2012.08.003
Llorens EM, Frank EO (2003) El fuego en la Provincia de La Pampa. In: Kunst R, Bravo S, Panigatti JL (eds) Fuego en los Ecosistemas Argentinos. Instituto Nacional Tecnologia Agropecuaria, Santiago del Estero, Argentina, pp 259–268
Loggio H (1992) Incendios en montes naturales en el Departamento de General Alvear. Multequina 1:193–196
Mahood AL, Balch JK (2019) Repeated fires reduce plant diversity in low-elevation Wyoming big sagebrush ecosystems (1984–2014). Ecosphere 10(2):e02591. https://doi.org/10.1002/ecs2.2591
Manzo-Delgado LL, López-García J (2020) Análisis espacial y temporal de áreas quemadas en 1998, 2003 y 2015 en la Reserva de la Biosfera Montes Azules, Chiapas, México. Bosque 41(1):11–24. https://doi.org/10.4067/S0717-92002020000100011
Miller JED, Safford HD (2020) Are plant community responses to wildfire contingent upon historical disturbance regimes? Glob Ecol Biogeo 29:1621–1633. https://doi.org/10.1111/geb.13115
Moghli A, Santana VM, Baeza MJ, Pastor E, Soliveres S (2022) Fire recurrence and time since last fire interact to determine the supply of multiple ecosystem services by Mediterranean forests. Ecosystems 25:1358–1370. https://doi.org/10.1007/s10021-021-00720-x
Mooney CZ, Duval RD (eds) (1993) Bootstrapping: a nonparametric approach to statistical inference. Sage Newbury Park, California, United States of America
Nakicenovic N, Davidson O, Davis G, Grübler A, Kram T, La Rovere EL, Metz B,Tsuneyuki Morita T, Pepper W, Pitcher H, Sankovski A, Shukla P, Swart R, Watson R, Zhou D (2000) Special report on emissions scenarios. A special report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom
Pausas JG, Bradstock RA (2007) Fire persistence traits of plants along a productivity and disturbance gradient in Mediterranean shrublands of south-east Australia. Glob Ecol Biogeo 16:330–340. https://doi.org/10.1111/j.1466-8238.2006.00283.x
Pausas JG, Bradstock RA, Keith DA, Keeley JE, Hoffman W, Kenny B, Llore F, Trabaud L (2004) Plant functional traits in relation to fire in crown-fire ecosystems. Ecology 85:1085–1100. https://doi.org/10.1890/02-4094
Pontius RG, Millones M (2011) Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. Int J Remote Sens 32:4407–4429. https://doi.org/10.1080/01431161.2011.552923
Pricope NG, Binford MW (2012) A spatio-temporal analysis of fire recurrence and extent for semi-arid savanna ecosystems in southern Africa using moderate-resolution satellite imagery. J Environ Manage 100:72–85. https://doi.org/10.1016/j.jenvman.2012.01.024
Rasmussen KL, Zuluaga MD, Houze RA (2014) Severe convection and lightning in subtropical South America. Geophys Res Lett 41(20):7359–7366. https://doi.org/10.1002/2014GL061767
Rostagno CM, Defosse G, del Valle HF (2006) Postfire vegetation dynamics in three rangelands of Northeastern Patagonia, Argentina. Range Ecol Manage 59(29):163–170. https://doi.org/10.2111/05-020R1.1
Roy DP, Boschetti L (2009) Southern Africa validation of the MODIS, L3JRC, and GlobCarbon Burned-Area Products. IEEE Trans Geosci Remote Sens 47(4):1032–1044. https://doi.org/10.1109/TGRS.2008.2009000
Rundel P, Villagra PE, Dillon MO, Roig-Juñent SA, Debandi G (2007) Arid and semi-arid ecosystems. In: Veblen TT, Young K, Orme A (eds) The physical geography of South America. Oxford University Press, Oxford, United Kingdom, pp 158–183
Scholes RJ, Walker BH (1993). Fire. In: Scholes RJ, Walker BH (eds) An African Savanna. Synthesis of the Nylsvley study. Cambridge University Press, Cambridge, United Kingdom, pp 111–124
Scott AC (2000) The Pre-Quaternary history of fire. Palaeogeo Palaeoclima Palaeoeco 164:281–329
Swetnam TW (1993) Fire history and climate change in giant sequoia groves. Science 262:885–889
Swetnam TW, Betancourt JL (1998) Mesoscale disturbance and ecological response to decadal climatic variability in the American Southwest. J Clima 11:3228–3247. https://doi.org/10.1175/1520-0442(1998)011%3C3128:MDAERT%3E2.0.CO;2
Tacchini F, Olmedo F, Naldini E (2014) Zonificación de la Vegetación y de Áreas Ganaderas de la Zona Árida del Departamento de General Alvear. In: Tacchini (ed) Ganadería bovina de General Alvear. UNCuyo, Mendoza, Argentina, pp 23–35
Turner D, Ostendorf B, Lewis M (2008) An introduction to patterns of fire in arid and semi-arid Australia, 1998–2004. Range J 30:95–107. https://doi.org/10.1071/RJ07039
Turner D, Lewis M, Ostendorf B (2011) Spatial indicators of fire risk in the arid and semi-arid zone of Australia. Ecol Indic 11:149–167. https://doi.org/10.1016/j.ecolind.2009.09.001
Verhoeven EM, Murray BR, Dickman CR, Wardle GM, Greenville AC (2020) Fire and rain are one: extreme rainfall events predict wildfire extent in an arid grassland. Int J Wild Fire 29(8):702–711. https://doi.org/10.1071/WF19087
Villagra PE, Defossé GE, Del Valle HF, Tabeni MS, Rostagno CM, Cesca E, Abraham E (2009) Land use and disturbance effects on the dynamics of natural ecosystems of the Monte Desert: implications for their management. J Arid Environ 73:202–211. https://doi.org/10.1016/j.jaridenv.2008.08.002
Villagra PE, Alvarez JA (2019) Determinantes ambientales y desafíos para el ordenamiento forestal sustentable en los algarrobales del Monte, Argentina. Ecol Aus 29:146–155. https://doi.org/10.25260/EA.19.29.1.0.752
Warrens MJ (2015) Properties of the quantity disagreement and the allocation disagreement. Int J Remote Sens 36:1439–1446. https://doi.org/10.1080/01431161.2015.1011794
Whelan R (1995) The ecology of fire. Cambridge University Press, Cambrigde, United Kingdom
White PS, Pickett ST (1985) Natural disturbance and patch dynamics: an introduction. In: Pickett ST, White PS (eds) The ecology of natural disturbance and patch dynamics. Academic Press, San Diego, United States of America, pp 3–13
Zar JH (1984) Biostatistical analysis. Prentice-Hall International Editions, Englewood Cliffs, New Jersey, United States of America
Zhang ZX, Zhang HY, Zhou DW (2010) Using GIS spatial analysis and logistic regression to predict the probabilities of human-caused grassland fire. J Arid Environ 74:386–393. https://doi.org/10.1016/j.jaridenv.2009.09.024
Zinck RD, Johst K, Grimm V (2010) Wildfire, landscape diversity and the Drossel-Schwabl model. Ecol Model 221:98–105. https://doi.org/10.1016/j.ecolmodel.2008.12.026

Publisher's Note