

1 **Coupled effects of climate teleconnections on drought, Santa**  
2 **Ana winds and wildfires in southern California**

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20

21 **Abstract**

22 Projections of future climate change impacts suggest an increase of wildfire  
23 activity in Mediterranean ecosystems, such as southern California. This region  
24 is a wildfire hotspot and fire managers are under increasingly high pressures to  
25 minimize socio-economic impacts. In this context, predictions of high-risk fire  
26 seasons are essential to achieve adequate preventive planning. Regional-scale  
27 weather patterns and climatic teleconnections play a key role in modulating fire-

28 conducive conditions across the globe, yet an analysis of the coupled effects of  
29 these systems onto the spread of large fires is lacking for the region. We  
30 analyzed seven decades (1953-2018) of documentary wildfire records from  
31 southern California to assess the linkages between weather patterns and  
32 climate modes using various statistical techniques, including Redundancy  
33 Analysis, Superposed Epoch Analysis and Wavelet Coherence. We found that  
34 high area burned is significantly associated with the occurrence of adverse  
35 weather patterns, such as severe droughts and Santa Ana winds. Further, we  
36 document how these fire-promoting events are mediated by climate  
37 teleconnections, particularly by the coupled effects of ENSO and AMO.

38

39 **Keywords:** SPEI, western USA, adverse weather, climate modes, wildfires

## 40 **1. Introduction**

41 The interannual variability in both large wildland fire occurrence and burned  
42 area is usually high in most ecosystems around the globe (Giglio et al., 2010).  
43 This phenomenon can be partially explained by the interaction between fire and  
44 annually-variable modes of sea surface temperature (SST) and related climate  
45 teleconnections (CTs; i.e. statistically significant climate remote responses far  
46 away from the forcing region, either concurrent with or time lagged; Kitzberger  
47 et al., 2007; Mariani et al., 2018, 2016; Schoennagel et al., 2005). However,  
48 these associations are not straightforward (Keeley, 2004) and underlying  
49 interactions among CTs may lead to specific modulations or amplifications  
50 (Ascoli et al., 2020; Wang et al., 2014) with varying effects on fire-prone  
51 weather patterns at subcontinental scales, subsequently influencing fire activity  
52 (Harris and Lucas, 2019). Under a climate change scenario projecting many

53 regions on Earth towards an increase in wildfire activity (Moritz et al., 2012),  
54 understanding the effect of climate variability on large-wildfire occurrence is  
55 essential for an efficient long-term environmental resources planning, wildfire  
56 management and to properly forecast fire danger and risk during the fire season  
57 (Schoennagel et al., 2005).

58 The occurrence of drought, heat waves, high wind speed events and their  
59 combined effects are well-known contributing factors boosting fire danger in  
60 most fire-prone areas worldwide (Bowman et al., 2017; Cardil et al., 2015).  
61 Such events may be mediated by SST modes such as *El Niño Southern*  
62 *Oscillation* (ENSO), the *Pacific Decadal Oscillation* (PDO), or the *Atlantic*  
63 *Multidecadal Oscillation* (AMO) and associated CTs, from interannual to  
64 multidecadal time scales (Kitzberger et al., 2006; Li et al., 2016). CTs influence  
65 the atmosphere inducing cascading effects on local weather patterns across the  
66 globe (Chiodi and Harrison, 2015; Maleski and Martinez, 2018) and indirectly  
67 affect interannual variation in biomass production, vegetation phenological  
68 cycles and fuel moisture (Dannenberg et al., 2018; Kitzberger et al., 2017; Li et  
69 al., 2016).

70 To date, much research has been analyzing the links between CTs and  
71 seasonal weather conditions including effects coupled with temperature,  
72 precipitation, evapotranspiration, soil moisture and drought (Abatzoglou and  
73 Kolden, 2013; Johnson and Wowchuk, 1993; O'Brien et al., 2019; Skinner et al.,  
74 2002; Turco et al., 2017; Westerling et al., 2006). The association between CTs  
75 and fire disturbance has also recently drawn considerable attention, especially  
76 in fire-prone regions (e.g. Australia, western United States), and strong  
77 evidence supports the existence of a link between CTs and burned area in

78 many regions across the world (Aragão et al., 2018; Kitzberger et al., 2007;  
79 Mariani et al., 2018, 2016; Schoennagel et al., 2005). However, the interaction  
80 between CTs and their influence on burned area variability is difficult to unravel,  
81 since it depends on underlying modulations of the frequency, intensity and  
82 duration of specific weather events (Li et al., 2016). Moreover, the influence of  
83 CTs on burned area is non-stationary since the variability of the CT modes  
84 changes from interannual (ENSO) to multidecadal time periods (AMO and PDO)  
85 (Ascoli et al., 2020; Levine et al., 2017; Zanchettin et al., 2016).

86 Southern California is a wildfire hotspot in the western United States (Bowman  
87 et al., 2017), where the most destructive fires in its recorded history occurred in  
88 the 21<sup>st</sup> century, despite the increased wildland fire suppression expenditures  
89 (Liang et al., 2008). It is well known that increases in wildfire activity in this  
90 region have been associated to high fuel dryness due to global warming  
91 exacerbation of evaporative demand (Williams et al., 2019), drought frequency  
92 and severity (Dettinger et al., 2011, Bond et al., 2015; Seager et al., 2015) and  
93 extreme winds in Autumn (Goss et al., 2020). The conjunction of  
94 subcontinental-scale patterns of drought spells and Santa Ana Winds (SAWs)  
95 affecting burned area variability might be modulated by CTs and their  
96 interactions. However, little is known about coupled effects of major climate  
97 modes influencing burned area in southern California (Chikamoto et al., 2017;  
98 Keeley, 2004), and particularly in relationship to the local weather patterns  
99 promoting the largest fires in the region.

100 In this study, we aimed at disentangling the coupled effects of CTs and adverse  
101 weather conditions driving large wildfires across southern California during the  
102 last seven decades. Specifically, we address the following research objectives:

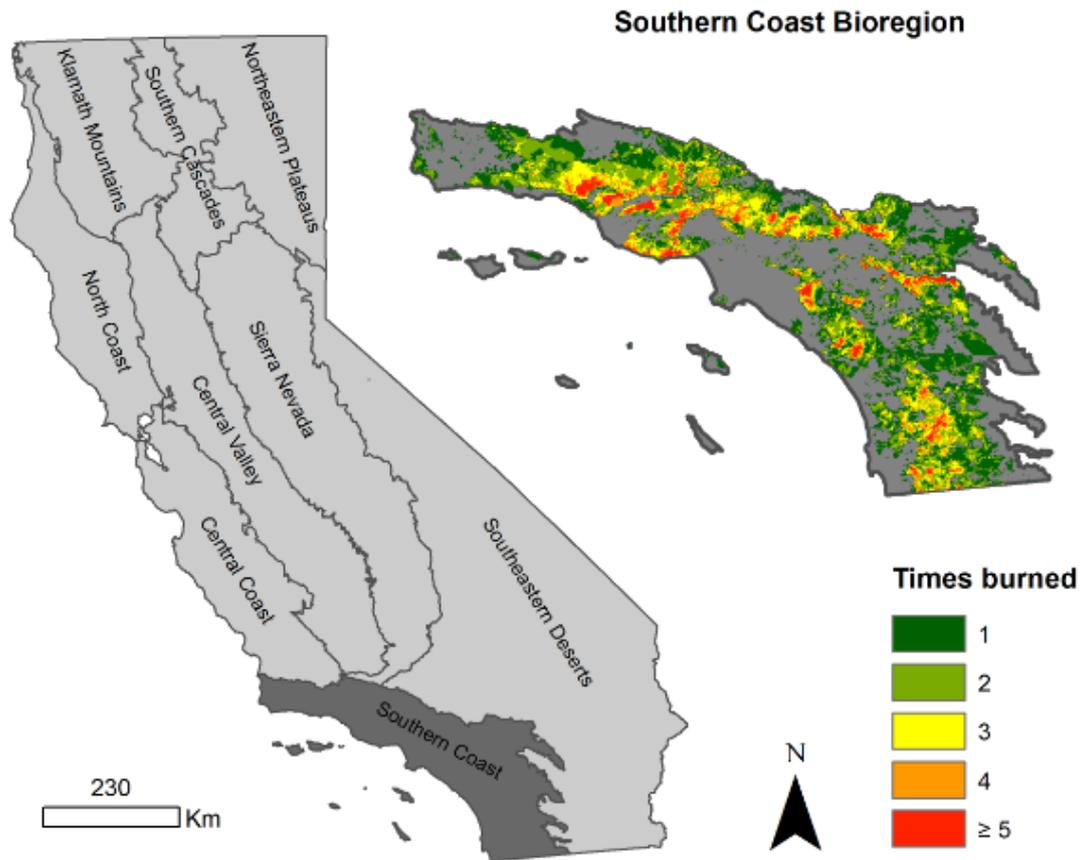
103 (1) To understand the effect of CTs in modulating long-term drought and SAWs;  
104 (2) To identify CTs patterns influencing the combined effect of drought and  
105 SAWs on large fire activity; and (3) To analyze seasonal fire-weather patterns  
106 throughout the year as influenced by CTs.

107

## 108 **2. Methods**

### 109 *2.1. Study Area*

110 The study area was the Southern Coast Bioregion in California, USA, where  
111 forest fires have dramatically affected both forested lands and urban  
112 settlements in the past decades (Figure 1). The region was defined based on  
113 the 9 bioregions outlined by Sugihara and Barbour (2006) who coalesced the 19  
114 sections described by Miles and Goudey (1997) considering consistent patterns  
115 of vegetation and fire regime for whole California. The region is dominated by  
116 Mediterranean climatic conditions, known to foster recurrent large fires (Pyne et  
117 al., 1998). Fire-prone weather situations such as long and dry summers with  
118 thunderstorms episodes, low relative humidity and strong winds are typical of  
119 this region (Sugihara and Barbour, 2006).



120

121 **Figure 1. Geographic location of the 9 bioregions delineated by Sugihara**  
 122 **and Barbour (2006) including the fire-prone Southern Coast Bioregion in**  
 123 **California** with the times the landscape was burned across the study area in  
 124 the study period (1953-2018) after superimposing all fire perimeters from CAL  
 125 FIRE (2019) used in this analysis.

126

127 *2.2. Data*

128 *2.2.1. Wildfires*

129 We used the Fire and Resource Assessment Program (FRAP) fire geodatabase  
 130 from CAL FIRE which includes historical fire perimeters since 1878 (CAL FIRE,  
 131 2019) and represents the most complete record of medium and large fire data in

132 California (Butry and Thomas, 2017). FRAP is developed by the US Forest  
133 Service Region 5, the Bureau of Land Management, the National Park Service,  
134 and CAL FIRE. The database includes timber fires greater than 0.04 km<sup>2</sup>, shrub  
135 fires greater than 0.20 km<sup>2</sup>, grass fires greater than 1.21 km<sup>2</sup>, and those  
136 wildland fires that destroyed at least three structures or caused more than US\$  
137 300,000 in damage. Fires larger than 1.21 km<sup>2</sup> in all vegetation types in the  
138 period 1953-2018 were selected for further analysis in this study. The selected  
139 sample guarantees homogenous and complete fire event records for statistical  
140 analysis.

#### 141 *2.2.2. Climate teleconnections*

142 In this paper, we addressed the effects of ENSO, AMO and PDO climate  
143 teleconnection signals on fire weather and activity in southern California from  
144 1953 to 2018. One of the most prominent CTs having impact on California is the  
145 ENSO with a 3- to 7-year cycle between warm (El Niño) and cold (La Niña)  
146 phases (Yoon et al., 2015). We used the Oceanic Niño Index (ONI) [ERSST.v5  
147 SST anomalies in the Niño 3.4 region (5° N to 5° S, 170° W to 120° W)], based  
148 on centered 30-year base periods updated every 5 years. The AMO is a long-  
149 term warming and cooling of North Atlantic SSTs with a cycle expanding over  
150 several decades (Enfield et al., 2001). The PDO is a Pacific climate  
151 teleconnection associated to changes in SST, sea level pressure, and wind  
152 patterns occurring in the northern Pacific Ocean causing widespread climatic  
153 variation over large areas of North America.

154 Data on all three CTs indexes was retrieved from the Climate Prediction Centre  
155 and the Earth System Research Laboratory of the National Oceanic and  
156 Atmospheric Administration (NOAA, 2019). The CT indexes were computed by

157 averaging monthly values (6-month running average) from December to May,  
158 after testing all possible running averaging windows and month combinations,  
159 such as the widely used 3-month running mean for December, January and  
160 February. According to the literature, ENSO index may have the strongest  
161 relationships with fire activity in winter-spring months since it accounts for  
162 potential lagged effects on spring and summer drought (Shabbar and Skinner,  
163 2004). This is especially relevant in a region where the window of storminess is  
164 narrow (typically between November and March), period during which most of  
165 the annual precipitation occurs (Cayan et al., 2016). To facilitate the analyses  
166 and interpretation of the findings, CTs were classified according to their positive  
167 and negative phases. Warm (ENSO>0.5; El Niño), neutral (ENSO between -0.5  
168 and 0.5) and cold (ENSO < -0.5; La Niña) periods for ENSO were classified  
169 based on a threshold of +/- 0.5°C. A warm or cold PDO/AMO phase  
170 corresponds to above or below zero values of the computed indexes,  
171 respectively. The temporal trend of the aforementioned indexes is shown in the  
172 supplementary materials (Figure S1 and S2).

### 173 *2.2.3. Drought data*

174 To account for drought conditions, we used the Standardized Precipitation  
175 Evapotranspiration Index (SPEI), a multiscale drought index that represents a  
176 climatic water balance by combining precipitation and potential  
177 evapotranspiration. SPEI data were retrieved from the global SPEI database  
178 (v2.5), based on the FAO-56 Penman-Monteith estimation of potential  
179 evapotranspiration (Vicente-Serrano et al., 2017). The database compiles SPEI  
180 data spanning from 1 to 48 months at a spatial resolution of 0.5 degrees (1950-  
181 2015) and 1.0 degrees (2016-2018). Previous work has found SPEI<sub>12</sub> as the

182 best overall drought hazard indicator (Blauhut et al., 2016). Accordingly, a 12-  
183 month accumulation period ( $SPEI_{12}$ ) was considered to depict yearly drought  
184 anomalies ( $SPEI_{12} < -0.85$ ), considering December as reference month.

#### 185 *2.2.4. Santa Ana wind data*

186 We used the Santa Ana Wind (SAW) dataset compiled by (Abatzoglou et al.,  
187 2013) available at <http://nimbus.cos.uidaho.edu/JFSP/pages/publications.html>  
188 from 1950 to present. Days with SAW conditions (SAD) were classified  
189 considering the criteria of a northeast–southwest sea level pressure gradient  
190 across southern California, and a strong cold air advection from the desert into  
191 the Transverse Range through daily data from the NCEP/NCAR Reanalysis  
192 dataset (Kalnay et al., 1996). We chose this dataset because it is representative  
193 for the study area, covers a longer period compared to other SAW datasets and  
194 has been validated with actual SAW events in the National Climatic Data Center  
195 storm database (Li et al., 2016).

196

#### 197 *2.3. Statistical analysis*

198 We performed several statistical analyses to (i) assess the relationships  
199 between CTs, weather patterns (SPEI and SAD) and fire incidence (burned  
200 area and fire size), and test the significance and magnitude of the observed  
201 relationships, (ii) and explore time-dependent associations between the  
202 aforementioned variables at inter-annual and seasonal levels. All statistical  
203 analyses and tests were conducted using the R software (R core development  
204 team, 2017).

### 205           2.3.1. *Redundancy analysis*

206    A redundancy analysis (RDA) was used to investigate potential associations  
207    between CTs, weather conditions (SPEI<sub>12</sub> and annual number of SAD) and  
208    burned area. Redundancy analysis is a multivariate approach widely used to  
209    model the association of a set of response variables to different factors. Similar  
210    to Principal Component Analysis (PCA), RDA decomposes the information into  
211    several dimensions depicting independent association patterns. Contrary to  
212    PCA, RDA allows specifying multiple variables as response, so that new  
213    dimensions portray the degree of association between the input driving factors  
214    and the targeted responses. More details about the technique can be found in  
215    (Legendre and Legendre, 2012). Two separate RDA models were fitted: firstly,  
216    to assess the association between burned area and CTs and, secondly, to  
217    gauge the association between burned area and seasonal weather conditions.  
218    The significance of the effect of constraints was analyzed through an ANOVA  
219    permutation test. RDA was conducted using the *vegan* R package (Oksanen et  
220    al., 2019).

### 221           2.3.2. *Superposed Epoch Analysis*

222    A Superposed Epoch Analysis (SEA) (*dpIR* package (Bunn et al., 2019)) was  
223    used to determine the significance of the departure from the mean and lagged  
224    years in terms of burned area for the different phases of the studied CTs  
225    through bootstrapped confidence intervals (Lough and Fritts, 1987) for a given  
226    set of key event years during the 1953–2018 period. We analyzed the effect of  
227    ENSO on lagged burned area considering both La Niña and El Niño years as  
228    events. Also, we tested its interaction with cold and hot phases of AMO and  
229    PDO. Given that both PDO and AMO show decadal oscillations, and SEA

230 requires annually-resolved data, we only included these modes in the SEA  
231 analysis in combination with ENSO (i.e., selecting as events those years with La  
232 Niña / El Niño and positive / negative AMO or PDO phases).

### 233 2.3.3. *Multigroup comparison tests*

234 The final step of our analysis aimed at detecting differences in fire size  
235 distribution and annual burned area among the different phases of CTs. We  
236 applied the multiple comparison test with unequal sample sizes by Kruskal and  
237 Wallis (Kruskal and Wallis, 1952) and a posteriori Dunn's test (Dunn, 1964) with  
238 *Bonferroni* correction. The  $H_1 > H_0$  hypothesis, indicates whether there is a  
239 statistical significance in fire size and annual burned area between any specific  
240 coupled CTs. Fire events were split among different coupled combinations of  
241 CTs phases (ENSO+/ENSO-, AMO+/AMO- and PDO+/PDO-), dry versus wet  
242 conditions and the presence/absence of SAW (fire activity during SAD and fire  
243 activity in no SAD). The resulting groups were submitted to the Dunn's test  
244 using fire size and burned area.

245

### 246 2.3.4. Wavelet coherence analysis

247 We used a wavelet coherence analysis to measure the intensity of the  
248 covariance of CTs and burned area patterns in the time-frequency space  
249 throughout the study period (Ascoli et al., 2020; Mariani et al., 2016). The test  
250 allows the detection of time-localized common oscillatory behavior of  
251 non-stationary signals through a cross-correlation between two time series as a  
252 function of time and frequency. In particular, to account for the coupled effect of  
253 CTs, we computed a combined index by running a Principal Component  
254 Analysis of AMO and ENSO. The PCA-eigenvector indicative of the alignment

255 of AMO+ and ENSO- phases was selected and yearly scores of the component  
256 used to test the wavelet coherence with the yearly burned area in spring-  
257 summer. The analysis was carried out using the R package *biwavelet* (Gouhier  
258 et al., 2016) using a Morlet continuous wavelet transform and considering the  
259 lag-1 autocorrelation of each series. The data were padded with zeros at each  
260 end to reduce wraparound effects. Significance of coherence at all frequencies  
261 lower than two years was tested using a time-average test with 2000 Monte  
262 Carlo randomizations.

263

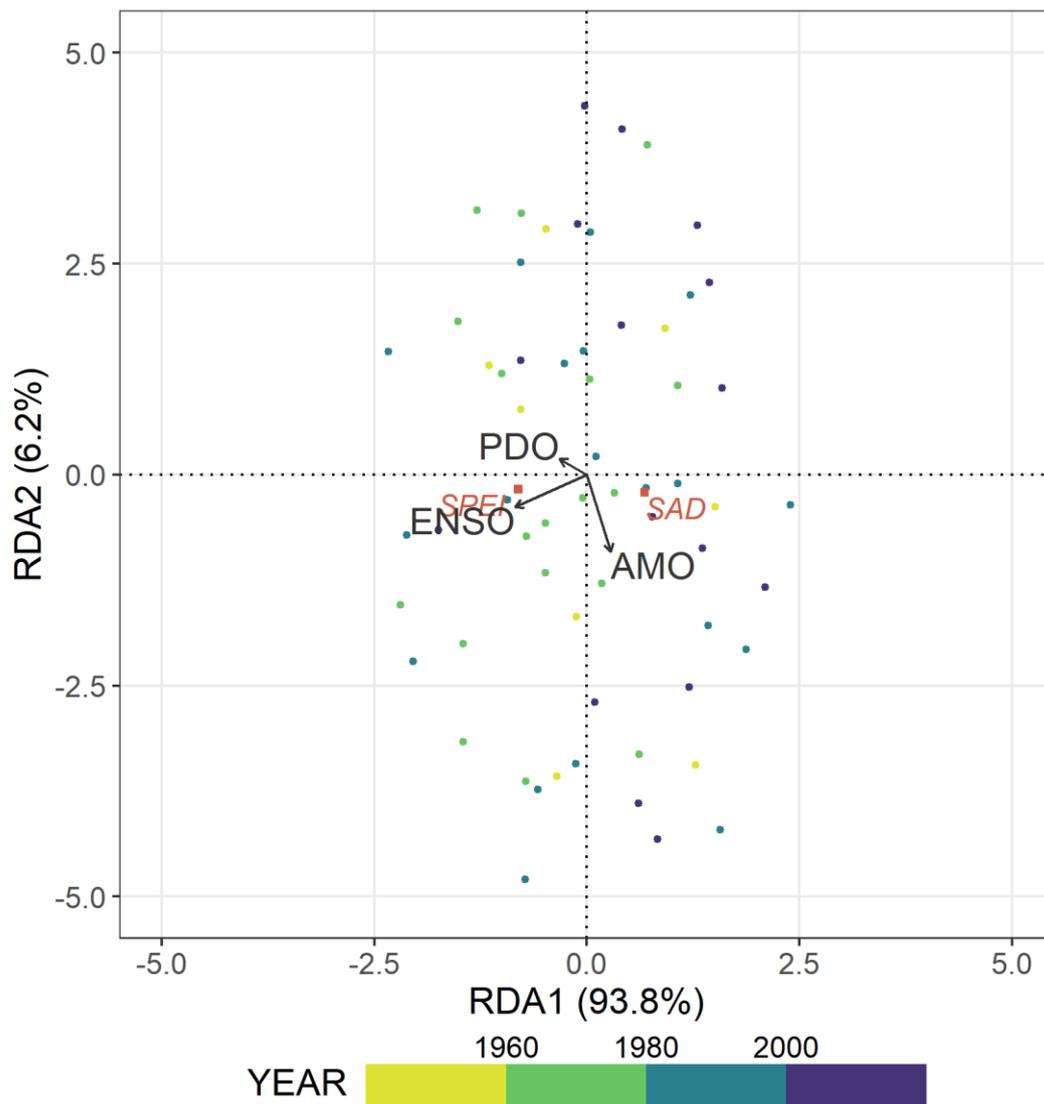
### 264 **3. Results**

#### 265 *3.1. Climate teleconnections, drought and Santa Ana winds*

266 The RDA analysis revealed interesting associations between CTs and fire-  
267 prone weather patterns (drought and annual number of SAD; Figure 2).  
268 Drought, represented by the SPEI<sub>12</sub> index, was positively correlated with ENSO  
269 ( $P < 0.01$ ), with higher drought conditions during La Niña phases than during El  
270 Niño events. The positive phase of AMO tended to be related with a higher  
271 annual number of SAD, but the relationship was not statistically significant ( $P =$   
272  $0.11$ ). PDO was not significantly correlated to either SPEI<sub>12</sub> or SAD.

273 We detected synchrony between drought conditions and the annual number of  
274 SAD (Figure 2, S1 and S2), so that larger annual burned areas occurred in  
275 those periods with coincident drought and SAW conditions (average annual  
276 burned area of 54,489 ha considering the 1983-1993 and 2002-2018 periods vs  
277 39,030 ha for the rest of years;  $P < 0.01$ ; see Figure S1).

278



279

280 **Figure 2. Redundancy analysis (RDA) bi-plot (1953-2018).** Points show  
 281 annual scores, vectors show climate teleconnection parameters (AMO, PDO  
 282 and ENSO) and red marks represent the response variables: drought (SPEI<sub>12</sub>)  
 283 and the annual number of Santa Ana winds (SAD).

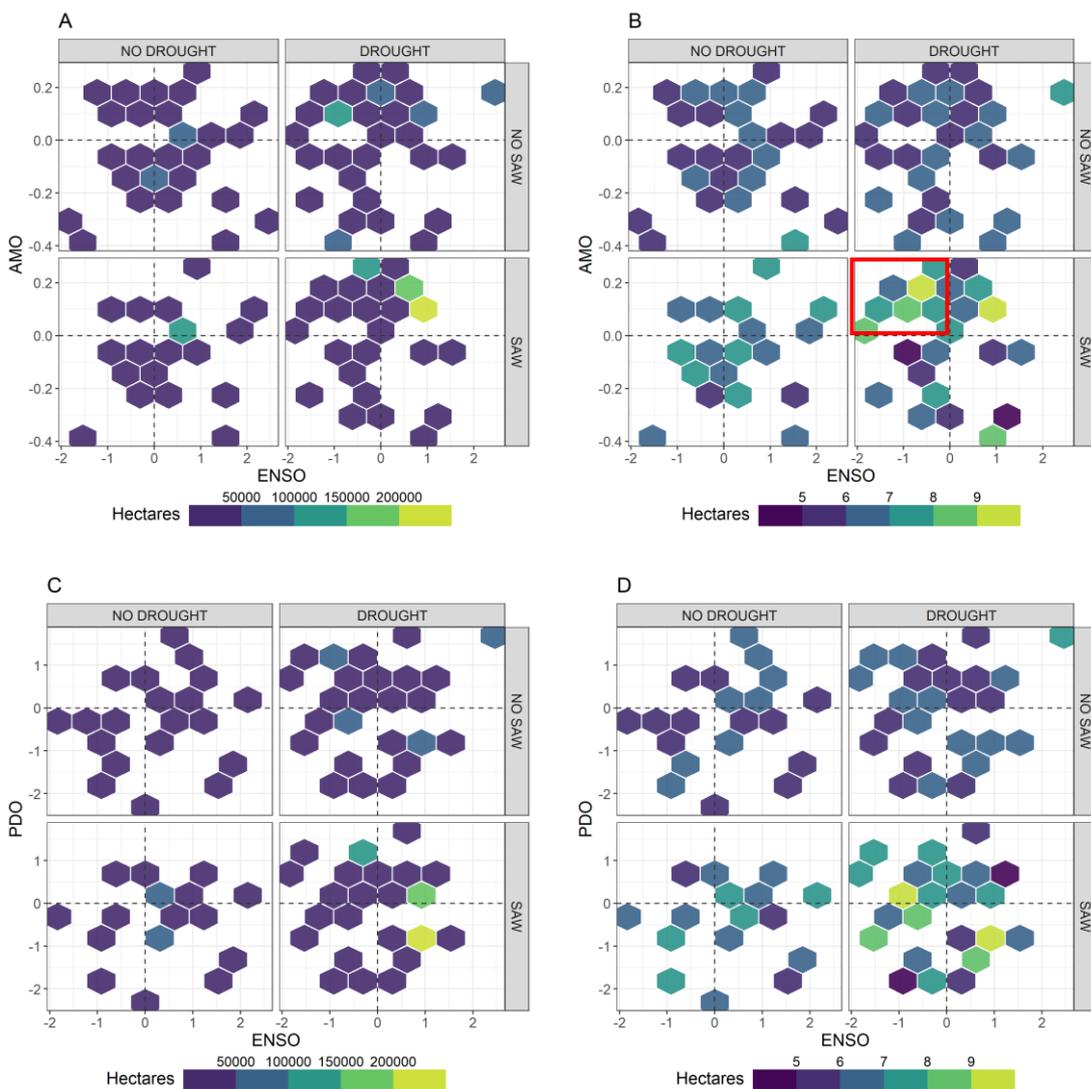
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### 285 3.2. Burned area, fire size and climate teleconnections

286 A total of 1,412 unplanned fires larger than 1.21 km<sup>2</sup> burned a total area of  
 287 2,995,092 ha in the study area during the period 1953–2018, with an average  
 288 fire size of 2,121 ± 182 ha. The annual burned area was significantly larger

289 under the positive phase of AMO ( $P = 0.049$ ; Figure 3A). A similar trend was  
290 found with PDO-, though statistically non-significant ( $P = 0.075$ ; Figure 3C). The  
291 SEA analysis revealed non-significant temporal relationships between annual  
292 burned area and the cold (La Niña) and warm (El Niño) phases of ENSO at any  
293 annual time lag, even though the SPEI<sub>12</sub> index was significantly correlated with  
294 ENSO as shown by the RDA analysis. However, based on the SEA analysis we  
295 found a significant synchronous effect between AMO+ and El Niño, resulting in  
296 larger annual burned area (time lag = 0 years;  $P = 0.04$ ), as shown in Figure 3A.  
297 The combined influence of SPEI<sub>12</sub> and SAW on both total burned area and  
298 median fire size was significant ( $P < 0.01$ ), being their effects modulated by  
299 certain CTs modes. A large fraction area (80%) was burned under drought or  
300 SAWs episodes. The portion of area burned under drought and SAWs was  
301 meaningfully dissimilar depending on the CTs phases. The largest fraction of  
302 burned area occurred under the conjunction of ENSO+, AMO+, drought and  
303 SAW conditions (Figure 3), with almost no influence of PDO. During El Niño  
304 period, the differences in burned area under SAW and non-SAW conditions  
305 were small, whereas during La Niña most of the burned area occurred under  
306 non-SAW conditions (75%). The burned area under La Niña was more closely  
307 associated with drought conditions (83.4%) compared to El Niño period  
308 (64.2%). Also, the distribution of burned area was asymmetrically negative for  
309 ENSO, with most fires occurring when ENSO was lower than 1 (Figure 3). The  
310 percentage of burned area in SAD and under drought conditions was higher for  
311 AMO+ than AMO-. The PDO followed a different pattern, with higher proportion  
312 of burned area under PDO- in those fires occurring under SAW and PDO+  
313 under drought conditions.

314 Fires were usually larger under SAW (P < 0.001) or drought conditions (P <  
 315 0.01), particularly in coincident drought and SAW situations (P < 0.01; Figure  
 316 3B and 3D). The median fire size was significantly larger during the positive  
 317 phase of AMO compared to its negative phase (P = 0.011). Also, those fires  
 318 that occurred under AMO+ and SAD were larger than those occurring under  
 319 AMO- or non-SAD (P < 0.01). These relationships between CT phases and fire  
 320 size did not occur under PDO and ENSO.



321 **Figure 3. Sum of burned area (panels A and C) and median fire size (log-**  
 322 **transformed; panels B and D) for each combination of CTs (AMO, PDO**

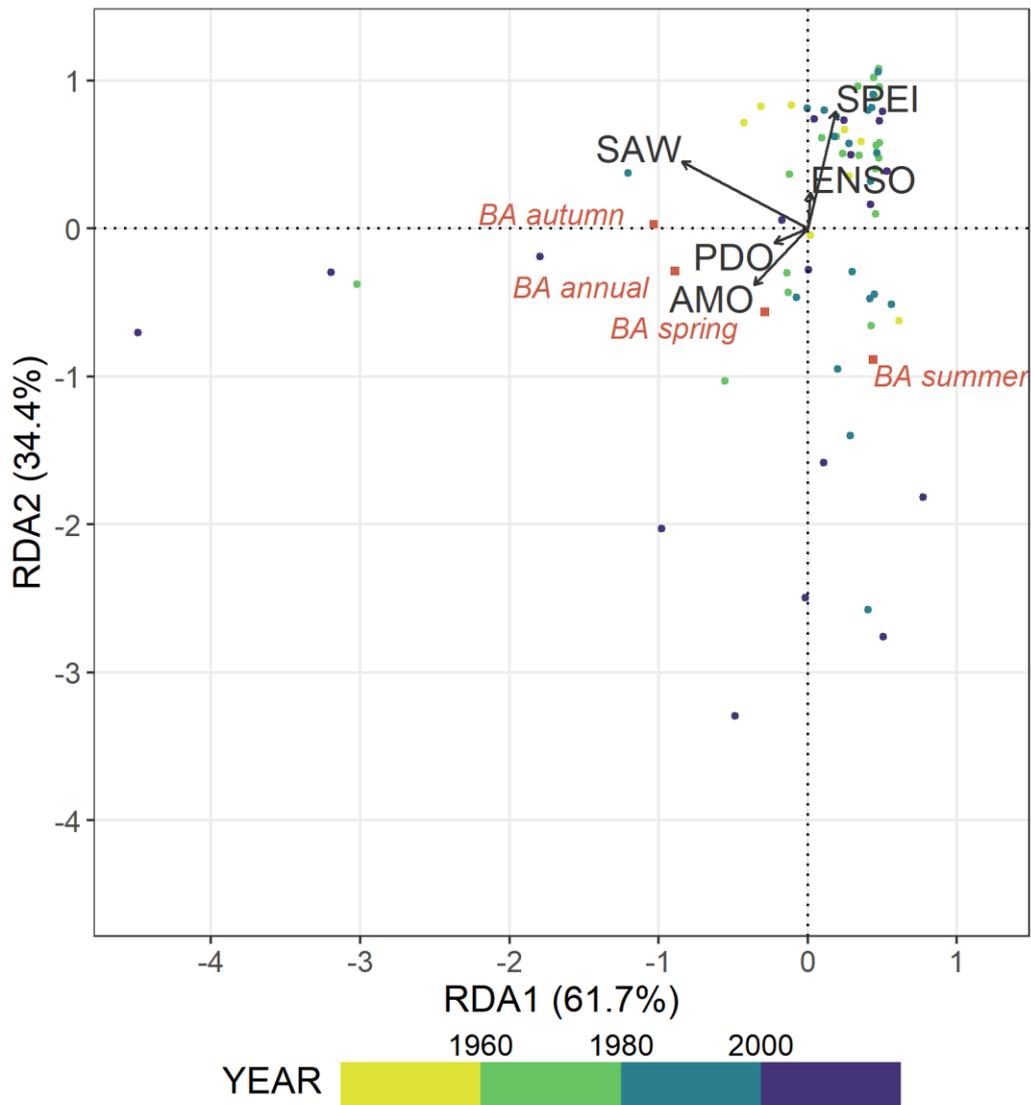
323 **and ENSO), SAW and drought (SPEI<sub>12</sub>)**. The highlighted pannel in red  
324 represents larger median fire size during La Niña, AMO+, SAW and drought  
325 conditions compared to other combinations.

326

### 327 *3.3. Seasonal burned area variability*

328 We found noteworthy seasonal differences in burned area modulated by CT  
329 modes and weather patterns (Figure 4). The area burned in autumn was  
330 significantly linked to SAW conditions ( $P < 0.01$ ) while the burned area in  
331 summer, and especially in spring, was significantly linked to drought ( $P = 0.03$ ).  
332 RDA outputs suggested an association between ENSO and SPEI. This finding  
333 was consistent with the results presented in Section 3.1 that showed a  
334 significant association between drought and ENSO. Nonetheless, despite the  
335 significant link between SPEI and ENSO, the association between ENSO and  
336 burned area was not significant in any season, as obtained from the SEA  
337 analysis.

338 The association between AMO and annual burned area was close to the  
339 chosen significance threshold in the RDA analysis ( $P = 0.059$ , threshold:  
340  $P < 0.05$ ), attaining similar p-values to the SEA analysis. Most of the burned area  
341 during autumn occurred under AMO+, SAW and mainly in combination with El  
342 Niño (Figure S3). The effect of PDO was non-significant ( $P = 0.11$ ).



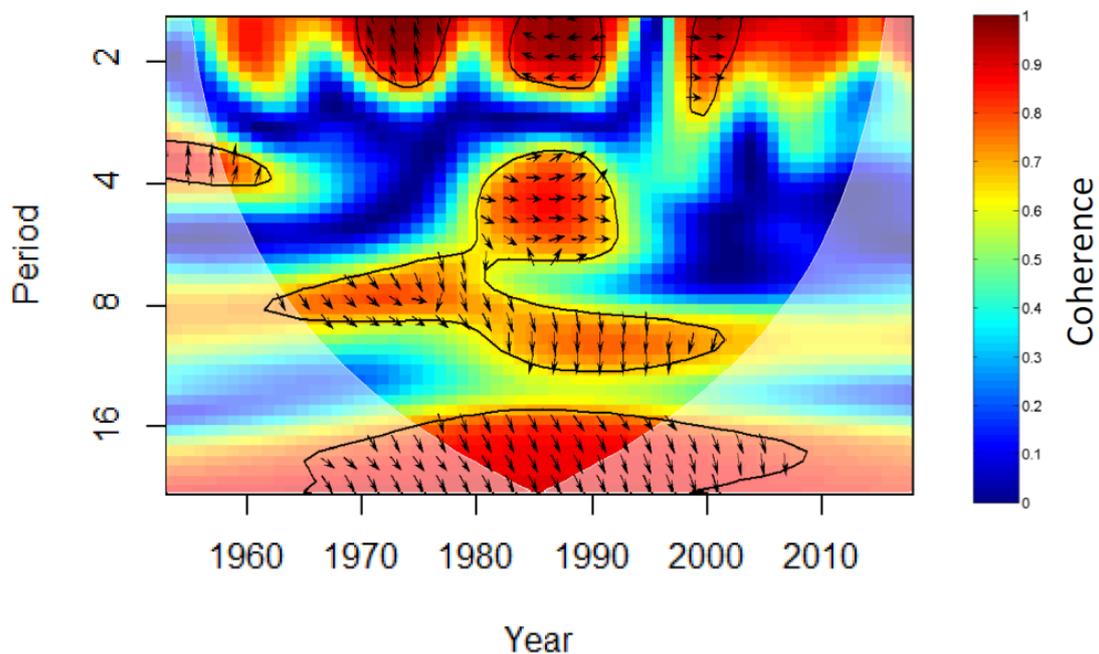
343

344 **Figure 4. Redundancy analysis (RDA) bi-plot (1953-2018).** Points show  
 345 annual scores, vectors show climate teleconnection (AMO, PDO and ENSO),  
 346 drought (SPEI<sub>12</sub>) and Santa Ana wind (SAW) parameters and red marks  
 347 represent the response variables: burned area (BA) in autumn, summer, spring  
 348 and annual.

349

350 The Wavelet coherence analysis between the combined CTs index  
 351 (AMO+/ENSO-) and burned area in summer and spring from 1953 to 2018  
 352 showed a significant coherence (Figure 5), which shifted from a period domain

353 of 8 years between 1960 and 1980 to a frequency of 2-6 years in more recent  
 354 decades (red regions with black contours in the graph). In these periods,  
 355 wavelet coherence showed an in-phase fluctuation (i.e., the two time series  
 356 move in the same direction) between the CTs coupled index and burnt area  
 357 (arrows pointing right) with AMO+/ENSO- mostly leading the oscillation (arrows  
 358 pointing down).  
 359



360  
 361 **Figure 5. Wavelet coherence between the combined teleconnection index**  
 362 **(AMO+/ENSO-) and burned area (spring and summer) in Southern**  
 363 **California.** The test analyzes the coupled effect of positive AMO and the cool  
 364 ENSO phase (La Niña) on the burnt area. Areas of strong coherence in time  
 365 between series are shown in red. Black contours designate frequencies of  
 366 significant coherence ( $p < .05$ , two-sided test) against red noise. Lighter  
 367 shading shows the cone of influence where edge effects are important. Arrows

368 pointing right show an in-phase behavior and arrows pointing down indicate a  
369 lead of the combined teleconnection index over the burned area.

370

#### 371 **4. Discussion and conclusions**

372 This study contributes to disentangling the effect of the main CTs and their  
373 synergies with local weather events such as drought and SAW in driving fire  
374 incidence (i.e., fire size and annual burned area) in southern California, by  
375 analyzing historical wildfires over the last 70 years. Our work confirms the  
376 importance of adverse weather conditions (i.e., drought and SAW) to explain  
377 burned area seasonally in southern California (Goss et al., 2020), and reveals  
378 that these relationships are mediated by CTs. The SPEI index was significantly  
379 correlated to ENSO positively, with wetter conditions found during El Niño years  
380 (Gergis and Fowler, 2009) due to increased precipitation in southern California  
381 (Allen and Anderson, 2018). This pattern may explain the seasonal burned area  
382 variability shown in this paper between the two phases of ENSO. While wildfires  
383 tended to occur during La Niña events under drought conditions, especially in  
384 spring and summer (Kitzberger et al., (2007) , during El Niño phases a  
385 substantial number of large fires burned during SADs in autumn. This finding is  
386 probably related to plant growth and fuel accumulation with higher development  
387 of biomass under wetter conditions in the preceding spring (Westerling et al.,  
388 2003).

389 The warm phase of AMO is associated with decreased precipitation and  
390 increased mean temperature in western United States. These conditions  
391 probably boosted larger annual burned area as showed the SEA and RDA  
392 analysis. Also, the patterns of interannual rainfall variability associated with

393 ENSO are significantly modulated between AMO phases. Enfield et al. (2001)  
394 found an increased positive correlation between ENSO and rainfall in southern  
395 California during the negative phase of AMO (1965–1994) as compared to its  
396 positive phase (1930–1959). This effect may explain the interaction found  
397 between AMO+, El Niño and annual burned area in the SEA analysis. In  
398 addition, the wavelet coherence analysis showed that the coupled  
399 AMO+/ENSO- index displayed a common non-stationary oscillation with the  
400 burnt area in spring and summer in southern California with periods ranging  
401 from 8 to 4 years, indicative of an amplification of La Niña during AMO+ phases  
402 with cascading effects on the fire regime.

403 Although we did not find any significant relationship between PDO, weather and  
404 fire activity, PDO may have a modulating effect on the climate patterns resulting  
405 from ENSO based on recent literature (Abiy et al., 2019; Margolis and  
406 Swetnam, 2013; Schoennagel et al., 2005; Wang et al., 2014). Wang et al.,  
407 2014 found that the climate signal of La Niña is likely to be stronger when PDO  
408 is highly negative, resulting in dry conditions in southern California; and,  
409 oppositely, highly positive PDO values would lead to El Niño-like wet conditions.  
410 Margolis and Swetnam (2013) found that ENSO influenced variability in  
411 moisture and upper elevation fire occurrence in the southwestern United States,  
412 and that such relationship could be potentially modulated by phases of PDO.

413 The RDA analysis suggests that the response of burned area to drought and  
414 SAW conditions is stronger in the 21<sup>st</sup> century compared to the second half of  
415 the 20<sup>th</sup> century, for fires occurring in the autumn under SADs and in summer  
416 with severe drought. This could be explained by the higher frequency of drought  
417 and SAW events in the 2000-2018 period, with AMO in its warm phase and

418 PDO in its cool phase (Figure S1 and S2), coupled with improved fire  
419 suppression capabilities (Liang et al., 2008) where only a few fires under  
420 extreme circumstances exceeded the initial attack and become large.

421 In the current context facing the impending effects of climate change, fire  
422 activity is projected to increase in Mediterranean biomes, such as in southern  
423 California (Moritz et al., 2012). On top of this, ENSO activity is projected to  
424 amplify due to anthropogenic climate change (Cai et al., 2015, 2014; Power et  
425 al., 2013), heralding a serious threat the ever expanding flammable rural-urban  
426 interface in this wildfire hotspot (Bowman et al., 2017). Our results highlight the  
427 coupled impacts of CTs on weather and burned area, revealing the need for  
428 considering the effects of AMO, which is projected to enter a negative phase  
429 during the next decades (Krokos et al., 2019), and PDO when using  
430 ENSO-based forecasts at seasonal scale. In light of future climate change  
431 pressures, we suggest that proper drought monitoring and SAD forecasting  
432 (through indexes such as SPEI) is needed to gauge the very beginning of dry  
433 periods, and by extent, the prediction of high-risk fire seasons to further assist  
434 decision makers.

435

## 436 **6. References**

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