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Visualizing Pyroclimatology

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Abstract

Background: Wildland fire activity often demonstrates distinct seasonality adhering to the alignment of climatologically favorable fuels, weather, and ignitions for wildfire or prescribed burning. Improved characterization of conditions that increase fire ignition probabilities, extreme fire behavior, and beneficial fire potential would enhance our understanding of fire regimes and provide insight for future wildland fire management.

Methods: We apply a commonly-utilized tool—the climograph—to visually communicate historical wildland fire activity by demonstrating fire seasonality, interannual variability, and past individual fire events at daily resolution using satellite observations to three distinct fire-prone and fire-requiring areas.

Results: Detection counts and cumulative fire radiative power in the resulting pyroclimographs provide first-order indicators of changes in fire activity occurring within- and out-of-season for the fire type (i.e., wildfires or prescribed burns). Using a case study of coastal Southern California, we show how pyroclimographs vary as the region of interest shifts and how their interpretation can be complemented by including climatological interpretations of additional fire environment data. Pyroclimographs also help characterize the fraction of fire radiative power—a proxy for emissions and burn severity—contributed from few or many events, i.e., the number of days contributing 50% or 90% of total fire radiative power since satellite observations began.

Conclusions: Information contained within a pyroclimograph may help track current conditions, identify factors associated with past fire occurrence, or understand typical timing of smoke impacts and their sources, all of which can be interpreted in the context of evolving real-time conditions and used for longer-term planning. Given the current ubiquity and projected increase of wildland fire in many regions, we recommend considering pyroclimographs as a visualization tool supporting varied applications where information regarding wildland fire seasonality and characteristics will benefit users.

Keywords: climatology, fire history, fire weather, remote sensing, visualization

1 Introduction

Climographs convey a region’s climatic seasonal cycle by displaying the monthly mean temperature range and total precipitation (e.g., Lasantha et al. 2022; Al-Yaari et al. 2023). Many regions also demonstrate a seasonal cycle of fire activity resulting from the annual march of plant phenology—a growing season when fuel accumulates and a dormant season when fuel becomes available for combustion—and the interplay of prolonged and short-term weather conditions. Fire events resulting from natural and human ignitions are linked by climate and punctuated by weather including the evolution of precipitation, temperature, snowpack, heat waves, humidity, and winds.

Visually linking the seasonality of environmental conditions to the cycle of fire danger for situational awareness has literally been in the pocket of firefighters as a ‘pocket card’ for over 20 years (Schlobohm 2000). The term ‘pyroclimograph’ arose from the juxtaposition of monthly mean temperature and precipitation with monthly

74 burned area (Swetnam et al. 2011). Sablan et al. (2024) developed similar visualiza-
75 tions of monthly fire activity to show the top 10th and bottom 10th percentiles and
76 mean of a historical record as well as highlight a particular year of interest. Sweeney
77 et al. (2025) generated weekly-timescale visualizations and separated prescribed burns
78 (i.e., pile and broadcast) from wildfires to show the distinct seasonalities of wildland
79 fire types.

80 However, many wildland fires, especially prescribed burns (Hatchett and Wells
81 2026) or damaging fast fires (Hantson et al. 2022; Balch et al. 2024) burn only for
82 hours or a few days, rendering aggregation to monthly or even weekly timescales poten-
83 tially misleading. These short timescales of burn periods may occur during periods
84 of increased fuel receptiveness amidst varied background environmental states, imply-
85 ing a climatological perspective also requires consideration of weather. During briefly
86 intensified fire activity, temporal aggregation limits our interpretation of how anomalous
87 the environmental conditions were compared to climatology. Understanding the
88 conditions leading to increased receptiveness of fuels and the potential for extreme fire
89 behavior may support fire management and community adaptation efforts at annual
90 to decadal timescales as well as characterizing a region’s general fire environment. This
91 is important for safely and effectively conducting prescribed burning (Worsnop et al.
92 2026), a necessary component for achieving wildfire resiliency and restoring ecosystem
93 function in fire-dependent regions. Further, understanding fire seasonality may inform
94 ideal times to promote campaigns for smoke-ready communities and other community
95 fire prevention, mitigation, and preparedness efforts.

96 Over two decades of satellite-based fire detections at subdaily timescales make it
97 possible to produce climatologies of fire activity at daily resolution for a user-defined
98 region. Regions can reflect operational needs or efforts supporting emergency and
99 resilience planning. For example, a region could be jurisdictionally defined, such as a
100 county or National Weather Service (NWS) County Warning Area (CWA). It could
101 also be physically-defined such as a watershed, ecoregion (Omernik and Griffith 2014),
102 mountain range (Snethlage et al. 2022), or pyrome (Short et al. 2020). Ultimately, the
103 goal is to provide a flexible capability—a regionally-relevant pyroclimograph at daily
104 resolution—for visualizing environmental conditions associated with past fire activity
105 and the timing of varied fire types (e.g., prescribed burns and wildfire). Decision
106 support opportunities include operational fire management, prescribed burn planning,
107 community messaging for wildfire prevention and preparedness, smoke readiness, long-
108 term adaptation and mitigation efforts for hazard reduction, or research activities to
109 better understand conditions supporting varied fire ignition and behavior patterns.

110 This brief report provides four examples of the construction and interpretation of
111 pyroclimographs utilizing fire detection data to gain insights about fire activity in three
112 fire-prone landscapes. First, we construct pyroclimographs to illustrate fire activity
113 in Colusa County, California, a region with distinct wildfire and prescribed burning
114 seasonality. Second, we show how pyroclimographs can document the near-real-time
115 progression of a fire season in the U.S. Southern Great Plains. Third, we show how
116 results, particularly seasonality, vary across different geographic delineations in coastal
117 Southern California. Fourth, we demonstrate how a more complete pyroclimograph
118 will incorporate ancillary fire environment data.

119 2 Data

120 We used satellite fire detections from the Moderate Resolution Imaging Spectro-
121 radiometer (MODIS) onboard the Terra and Aqua spacecraft (Giglio et al. 2016)
122 and acquired from the NASA Fire Information for Resource Management System
123 (<https://firms.modaps.eosdis.nasa.gov/>) for the period spanning 1 January 2001 to 1
124 April 2026. County shapefiles were acquired from the U.S. Census Bureau (<https://www2.census.gov/geo/tiger/TIGER2025/COUNTY/>). Shapefiles for the NWS CWAs
125 were acquired from the NWS County Warning Boundary Area Dataset ([https://www.
126 weather.gov/gis/CWABounds](https://www.weather.gov/gis/CWABounds)). The Southern California Mountains/Northern Baja
127 pyrome was extracted from (Short et al. 2020). Environmental Protection Agency
128 (EPA) Level 3 ecoregions (Omernik and Griffith 2014) were acquired from [https://
129 www.epa.gov/eco-research/level-iii-and-iv-ecoregions-continental-united-states](https://www.epa.gov/eco-research/level-iii-and-iv-ecoregions-continental-united-states). Last,
130 we used a boundary delineating the Santa Monica Mountains, a subset of the
131 Transverse Ranges and excluding the Palos Verdes Hills, from the Global Mountain
132 Biodiversity Assessment Mountain Inventory version 2.0 (Snethlage et al. 2022).
133

134 To more fully characterize the fire environment, we used hourly observations of 2-m
135 air temperature, 2-m relative humidity and 6-m (~ 20 ft) wind speed from the Malibu
136 Hills, California Remote Automatic Weather Station (RAWS; acquired from the West-
137 ern Regional Climate Center at: <https://raws.dri.edu>) for the station’s period-of-record
138 (January 1995–February 2026) to capture the spread component. Daily, gridded ~ 4
139 km horizontal resolution estimates of energy release component spanning 1979–2025
140 were acquired from the gridMET product (Abatzoglou 2013) to capture the ignition
141 component.

142 3 Methods

143 Analysis of fire detection latitude, longitude, fire radiative power (FRP), and time of
144 detection, as well as other fire environment data, was performed using Matlab (The
145 MathWorks Inc. 2024). Desiring maximum detectability, we did not omit detections
146 based on confidence values, which may include anomalous detections due to industry
147 or sun glint. For each calendar day across all years, the total number of detections are
148 counted and reported by a bar chart (Figures 1b,d); specific years of interest can be
149 plotted separately. Similarly, cumulative FRP across each calendar day in the period-
150 of-record is calculated to show seasonality of fire activity (right hand y-axis of Figures
151 1b and d). Lastly, we calculate the total FRP over the period of record and then sort
152 the daily FRP entries in descending order to determine the number of days that it
153 took to reach the 50%, 75%, and 90% of the total FPR (text beneath Figures 1b,d).
154 While 1 January was selected as the starting point, depending on user needs, much
155 like water years, the ‘fire year’ could be expressed as a ‘wind year’ that orients the
156 peak windy season in the center of the figure.

157 To show the seasonality of fire danger in the Santa Monica Mountains exam-
158 ple (Figure 3), gridMET-based estimates of energy release component (ERC) were
159 extracted for a box encompassing the region (Figure 3b). The 3rd, 5th, 20th, 50th,
160 80th, and 97th percentiles were calculated between 1979–2025 at a daily scale (plotted

161 with 5 day running mean to smooth the data). The 3rd, 50th, and 97th percentiles
162 were calculated across all days.

163 Last, fire weather hours were estimated using the available summed daily number
164 of hours between 1995–2024 meeting either set of criteria for a Red Flag Warning
165 at the NWS Fire Weather Zones (FWZ) 369 and 370 (California Annual Operating
166 Plan 2025): 1) relative humidity $\leq 10\%$ with sustained wind speed $\geq 6.7 \text{ m s}^{-1}$ (\geq
167 15 miles hr^{-1}) or gusts $\geq 11.2 \text{ m s}^{-1}$ ($\geq 25 \text{ miles hr}^{-1}$) or 2) relative humidity $\leq 15\%$
168 with sustained wind speed $\geq 11.2 \text{ m s}^{-1}$ ($\geq 25 \text{ miles hr}^{-1}$) or gusts $\geq 15.6 \text{ m s}^{-1}$
169 ($\geq 35 \text{ miles hr}^{-1}$). If these conditions are sustained for $> 6\text{hr}$ with critically dry fuels,
170 a Red Flag Warning may be issued. Under certain extreme conditions, forecasters will
171 coordinate with fire agencies to relax constraints for Red Flag Warning issuance.

172 4 Results

173 4.1 Pyroclimographs: A Simple Interpretation and Application

174 Colusa County, CA—an agricultural community—demonstrates three distinct burn
175 seasons as evidenced by small increases in annual accumulations of FRP during
176 late winter to early spring (mid-January–April), a more rapid increase during the
177 extended summer (late June–September), and a shift back to gradual but annu-
178 ally consistent increases during fall (October–November; Figure 1a). Following the
179 regional prescribed burn climatology produced by Worsnop et al. (2026) and examin-
180 ing wildfire history data hosted by CAL FIRE ([https://www.fire.ca.gov/what-we-do/
181 fire-resource-assessment-program](https://www.fire.ca.gov/what-we-do/fire-resource-assessment-program); not shown), we interpret the consistent daily detec-
182 tions (Figure 1b) with lower FRP as indicating the seasonal nature of planned
183 agricultural burning and prescribed burning of wildlands during spring and fall, while
184 more brief instances of higher FRP indicate named summer wildfire incidents (e.g.,
185 2012, 2018, and 2024). Incorporating additional agency (or other) records of prescribed
186 burns versus wildfire events is recommended to differentiate the seasonality of fire
187 types.

188 Wildfire and prescribed fire occur in the U.S. Southern Great Plains throughout the
189 year, though a peak in fire activity occurs in February following the dry winter season
190 and terminates with the onset of the spring convective season in April (Figure 1c–d).
191 As fire detection data is made publicly available on the order of hours after a satellite
192 overflight, pyroclimographs can be used to track the progression of a fire season in
193 near-real-time. With persistent drought and heavy fine fuel loading priming the fire
194 environment, a dry and windy spring initiated the 2026 wildfire season approximately
195 two weeks early based on the available climatological data record (red line in Figure
196 1c). While the annual cumulative curves (Figures 1a and 1c) allow the comparison of
197 years against one another—for example, to identify early onset of fire activity—for the
198 remainder of the manuscript, we focus on the detection bar charts (Figure 1b and 1d).

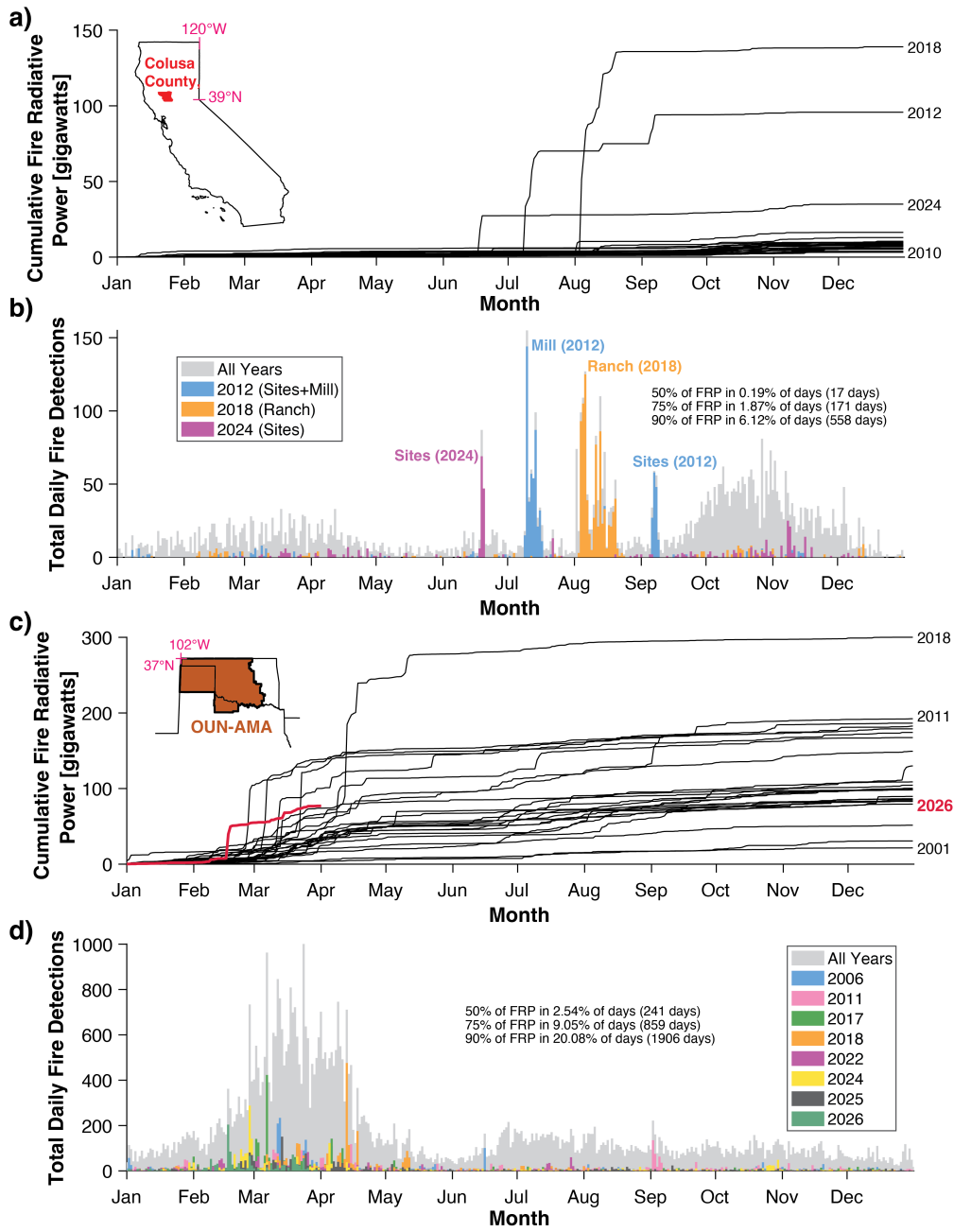


Fig. 1 (a) Pyroclimograph showing daily cumulative fire radiative power for each calendar year (2001–2025; highest three and lowest year shown) for Colusa County, California. (b) Period-of-record total daily fire detections across years (gray bars). Contributions from notable fires are colored. (c–d) As in (a–b) but for the Norman, Oklahoma (OUN) and Amarillo, Texas (AMA) NWS CWAs (2026 shown in bold red).

199 4.2 Variability across coastal Southern California

200 Coastal Southern California is a densely populated, fire-prone but ignition-limited
201 landscape with extraordinary exposure of values-at-risk to wildland fire. Here, we
202 explore how pyroclimographs contribute to fire history interpretation across different
203 domains within this larger region. Starting at the largest scale, the Southern California
204 Mountains/Northern Baja pyrome spans interior Santa Barbara County to San Diego
205 County (Figure 2a). This large region has experienced many notable wildfires between
206 May and early January, but also shows evidence of cool season prescribed burning
207 (consistent but few detections). Two EPA Level 3 Ecoregions comprise the pyrome. In
208 the mid-to-higher elevation, conifer-dominated Southern California Mountains ecore-
209 gion, fire season typically spans June to mid-October but can include anomalous dry
210 downslope Santa Ana wind-driven fire events such as the late October firestorms in
211 2003 and 2007 as well as the December 2017 Thomas Fire and January 2025 Los
212 Angeles Palisades and Eaton Fires (Figure 2b). The lower elevation, chaparral and
213 coast sage and chaparral-dominated Southern California Coast/Northern Baja ecore-
214 gion has fewer fires in the summer (one exception being the 2018 Holy Fire), owing
215 to cool and moist marine layer influences (Figure 2c). Wildfires are most common in
216 late fall and into winter if Santa Ana winds begin before season-ending precipitation
217 occurs in October or November (Cayan et al. 2022).

218 The NWS Los Angeles CWA (Figure 2d) includes more interior dry regions and
219 elevated terrain susceptible to human and lightning ignitions that yield a longer
220 overall fire season from May through early January with a notable peak in activity
221 between July and September. Similar to the coastal regions, delayed winter precipita-
222 tion exposes the region to a higher probability of large wildfires associated with dry
223 and windy Santa Ana conditions from October–January. This sequence contributed
224 to both the 2003 and 2007 October firestorms, the November 2018 Woolsey Fire, and
225 two major southern California winter season fires: the Thomas Fire and the Palisades
226 and Eaton fires.

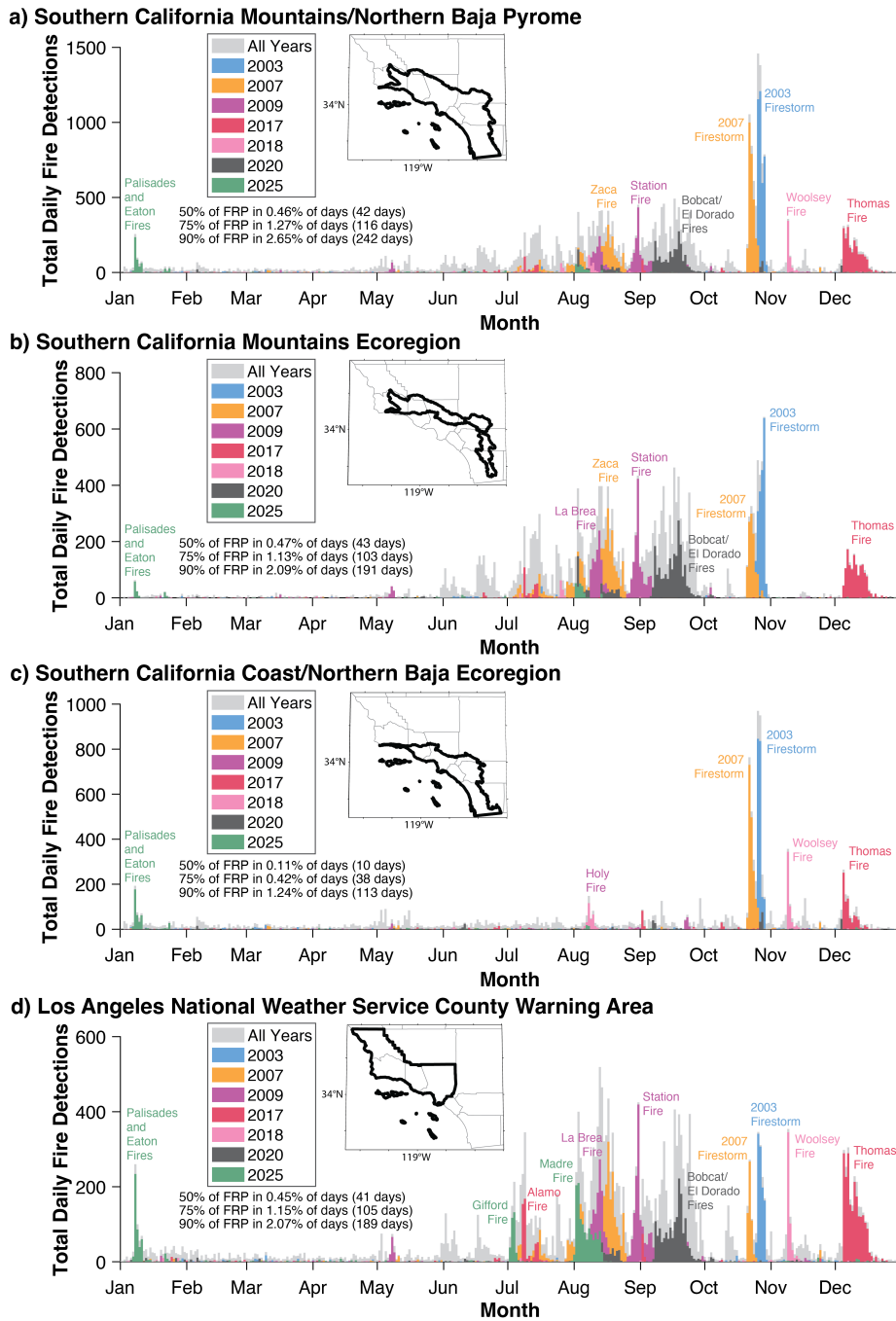


Fig. 2 (a) Pyroclimograph showing daily cumulative fire radiative power for each calendar year (2001–2025; highest three and lowest year shown) for Colusa County, California. (b) Period-of-record total daily fire detections across years (gray bars). Contributions from notable fires are colored. (c–d) As in (a–b) but for the Norman, Oklahoma (OUN) and Amarillo, Texas (AMA) NWS CWAs (2026 shown in bold red).

227 4.3 Towards a more complete pyroclimograph

228 Our motivation to extend the monthly-scale pyroclimograph proposed by Swetnam
229 et al. (2011) is to provide a more complete picture of fire activity and the fire envi-
230 ronment at daily timescales and merge this information with the classic pocket card
231 style (Schlobohm 2000). The Santa Monica Mountains of Ventura and Los Angeles
232 counties represent an ideal location to demonstrate how fire weather deviates from
233 climatological mean conditions. Here, strong winds and low relative humidity condi-
234 tions associated with occasional offshore, downslope Santa Ana winds—especially when
235 winds occur before season-ending rainfall (Cayan et al. 2022; Guirguis et al. 2025)—
236 produce extreme fire behavior, with 10 days contributing 90% of total FRP (Figure
237 3a). The number of days contributing to a given percentage of total FRP increases as
238 the domain grows larger (Figure 2–3). However, this calculation intends to indicate
239 whether a relatively small number of days (10 days in the Santa Monicas, or 145–242
240 days in the larger coastal Southern California regions; Figure 2) or a large number of
241 days (1,906 days in the OUN–AMA region; Figure 1d) contribute to various fractions
242 of total FRP to provide a simple metric of the frequency and intensity of fire in a
243 region.

244 Merging the fire detection climatologies (Figure 3a) with an ERC climatology
245 extends and modernizes the original pocket card (Schlobohm 2000) by including the
246 full fire climatology for comparison with ERC percentiles calculated for days of the year
247 and across the year (Figure 3b). The seasonal cycle of ERC indicates a peak during
248 winter and a minima during summer; similarly, the largest range in values occurs in
249 winter and smallest range during summer. The timing and magnitude of these ranges
250 results from the Mediterranean climate and proximity to summer marine influences.
251 Plotting the range-mean ERC on the ignition dates of notable recent Santa Monica
252 fires (and two nearby high-impact fires, the 2017 Thomas Fire and 2024 Mountain
253 Fire) show that most fire activity occurs in late fall through early winter, the exception
254 being the Springs Fire that occurred during a late season wind event. These fires all
255 ignited on days with above normal ERCs but none exceeded the 97th percentile and
256 many were below the annual 90th percentile.

257 Until now, pyroclimographs have focused on the ignition component of the fire
258 environment. Inclusion of wind, and particularly wind associated with low relative
259 humidity, incorporates the spread component. Using the two sets of relative humidity
260 and wind criteria for Red Flag Warnings but omitting the wind duration constraint,
261 fire weather hours are relatively rare from May–September before reaching peak fre-
262 quency during October–November (Figure 3c). They decline through the winter before
263 a secondary peak between March–April, albeit typically when live fuel moisture is
264 high. Just as the ERC climatology highlighted the marine stratus season, fire weather
265 hours highlights two critical fire weather patterns affecting the Santa Monicas: the
266 fall–winter Santa Ana season, followed by a signal of late spring Sundowner Winds
267 that typically affect the Santa Ynez Mountains to the northwest (Hatchett et al. 2018)
268 but can also influence the Santa Monicas.

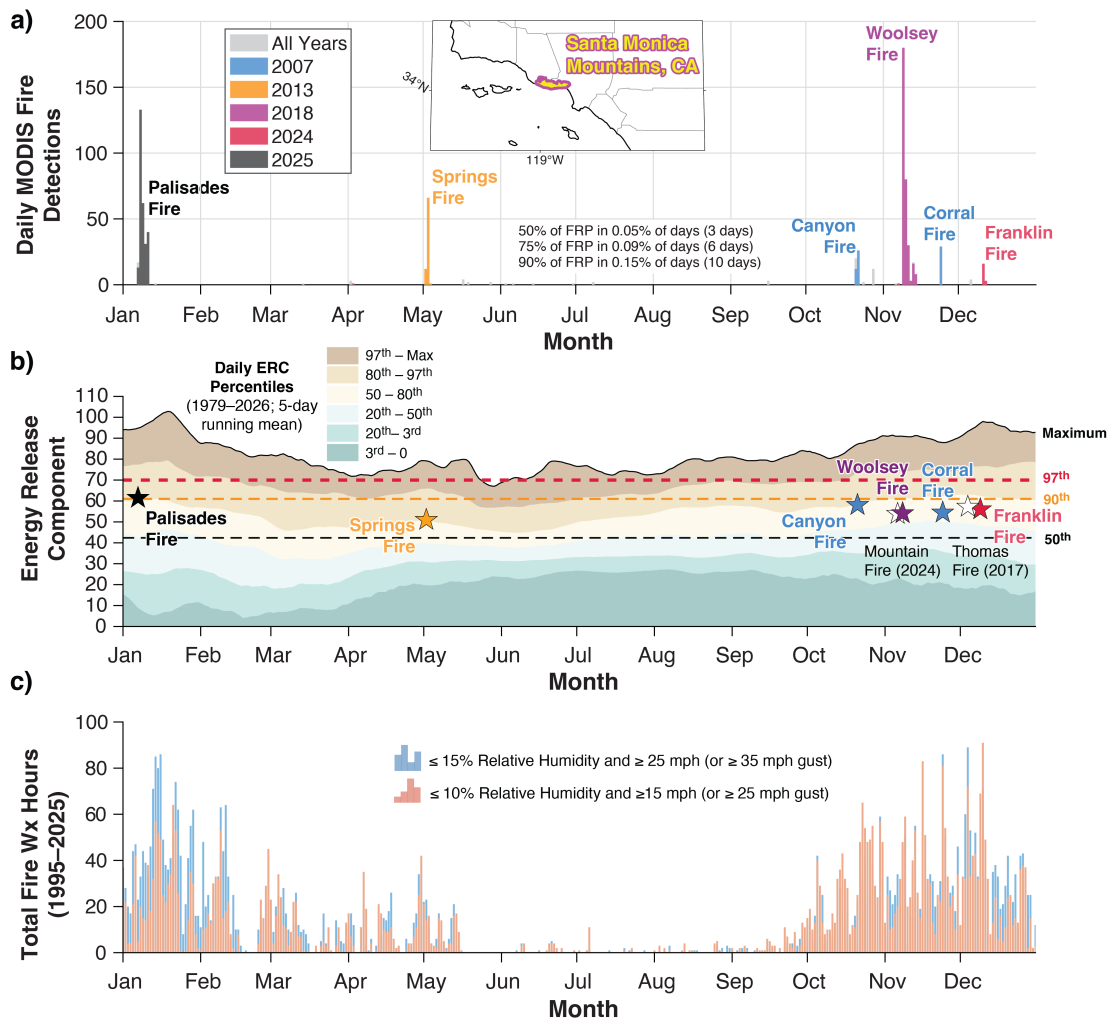


Fig. 3 Pyroclimograph showing period-of-record total daily fire detections (gray bars; left y-axis) for the Santa Monica Mountains of southern California (inset map). Contributions from notable named fires are colored by year. (b) Energy release component daily climatology with shaded regions representing percentile bins. Horizontal dashed lines represent all-time percentiles. For reference, the actual ERCs on the day of ignition for notable fires are provided; two other nearby damaging fires, the 2017 Thomas Fire and the 2024 Mountain Fire are also shown for reference. (c) Total fire daily weather hours spanning January 1995–February 2026 calculated using two sets of wind speed and relative humidity criteria for NWS LOX Red Flag Warnings at the Malibu Hills RAWs.

269 5 Discussion

270 Daily-scale pyroclimographs using satellite data provide a more temporally granu-
 271 lar and spatially explicit perspective than historical fire perimeters that offer only

272 singular dates of discovery and containment (Swetnam et al. 2011) or monthly aggre-
273 gations of satellite data (Giglio et al. 2009; Sablan et al. 2024). They also reveal
274 potential prescribed burn seasonality, assuming burning occurred during satellite over-
275 flight, through the interpretation of more frequent, low FRP detections. However,
276 integration of authoritative records of prescribed burning and wildfire are necessary
277 to ensure correct interpretations (Sweeney et al. 2025). Assuming a correct interpreta-
278 tion, pyroclimographs can serve as a training tool to understand a region’s satellite-era
279 fire history, identify ideal prescribed burning timing, extract information to examine
280 similarities and differences across regions such as fuels-driven versus wind-driven fire
281 location and timing, and as a tool to document and contextualize the evolution of a
282 fire season in terms of how observed fire weather deviated from normal conditions.
283 While we focused on satellite-era fire history, longer records of fire history could be
284 incorporated to increase the comprehensive nature of the pyroclimograph.

285 A limitation of our approach is that it visualizes a minimum amount of fire activity:
286 satellites may not detect all pixels burning at all times as wildland fire progresses
287 across the landscape. Nor can satellites identify fires that do not produce a detectable
288 heat signature (e.g., lower-intensity below-canopy burning). False positives due to
289 industry or sun glint may cause some overestimation of counts and require additional
290 investigation. An upcoming challenge for data continuity will be to merge MODIS
291 and the Visible Infrared Imaging Radiometer Suite (VIIRS) detection climatologies
292 as the MODIS mission approaches decommissioning and VIIRS becomes the primary
293 fire detection data source.

294 Reporting climatological mean conditions likely underestimates the potential for
295 fire activity, which may only require several hours to yield favorable conditions for
296 ignition and extreme fire behavior that presents resistance to control. It also prevents
297 clear identification of the frequency, timing, magnitude, and duration of anomalous
298 conditions favoring wildland fire. Because many fire-prone regions are characterized by
299 variability of environmental conditions across intraseasonal (winter wet spells versus
300 mid-winter dry spells followed by dry and windy Santa Anas), interseasonal (fall and
301 winter Santa Ana events versus summer drought or convective storms), and interan-
302 nual timescales, inclusion of fire weather variability, as done here using ERCs and fire
303 weather hours, only estimates the first-order potential for fire. Identifying the specific
304 conditions associated with burning will aid in the identification of the atmospheric
305 processes driving them, improving their predictability and thus community prepara-
306 tion. Subsequent iterations of pyroclimographs will include local conditions extracted
307 on the day (or hour) of burning to better assess their role during rapid fire spread or
308 high FRP events and how conditions influence burn severity (Orland et al. 2025).

309 6 Closing Remarks

310 We revisited the concept of pyroclimographs as simple visualizations leveraging satel-
311 lite fire detections to demonstrate a facet of pyrogeography: the “where of fire when”
312 to understand “the why of fire.” Providing a daily perspective of wildland fire activ-
313 ity, pyroclimographs contextualize a region’s satellite-era fire history and support the
314 interpretation of past fire events, especially when complemented with fire environment

315 data. With no additional information, a pyroclimograph indicates when fire activity
316 has not (yet) been observed, when fire activity may be common but less with lower
317 FRP (potential prescribed burning) versus infrequent but higher FRP (potential wild-
318 fire). By including fire environment-related data and its variability, a picture emerges
319 of why certain seasons typically do or do not have increased fire activity and why
320 anomalous events occurred. The simplicity of these visualizations is intentional; it is
321 our aim that they can be used not just for scientific or tracking purposes but also for
322 educational and training purposes for anyone willing to interpret a time series for the
323 appropriate domain.

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