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Visualizing Pyroclimatology

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Abstract

Background: Wildland fire activity often demonstrates distinct seasonality resulting from the alignment of climatologically favorable fuels, weather, and ignitions. Characterization of windows favoring extreme fire behavior and beneficial fire potential at relevant spatiotemporal scales provides context for interpreting fire regimes and informing wildland fire management.

Methods: Adapting the climograph concept into “pyroclimographs,” we utilize satellite observations of fire radiative power (*FRP*) and detection counts spanning 1 January 2001–15 September 2026 to visualize fire activity across daily-to-decadal timescales. We first present four regional case studies then evaluate cumulative 2026 *FRP* rankings and the temporal concentration of fire activity (days contributing 10–90% of total record *FRP*) across 50 U.S. states, 136 pyromes, and 117 National Weather Service County Warning Areas.

Results: Pyroclimographs reveal fire activity type and timing, which is sensitive to geographic delineations, and highlight distinct fire environments when complemented with additional data. In 2026 (through 15 September), we identify multiple regions of the U.S. experiencing record-high or record-low active fire years. Fire activity concentration varies widely across pyromes with 41 pyromes accumulating 90% of total *FRP* in under 2% of total days (< 187 days), while 30 pyromes required over 15% of days (> 1,406 days).

Conclusions: By contextualizing fire regimes across regions and timescales, pyroclimographs demonstrate potential for use as an operational and research visualization tool supporting aspects of fire management and public communication. Integrating satellite-based fire detections with additional data could augment firefighter Pocket Cards by enhancing their accessibility and usability.

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

1 Introduction

Conventional climographs display monthly mean temperature ranges and precipitation accumulations to convey a region’s annual climatic cycle (e.g., Lasantha et al. 2022; Al-Yaari et al. 2023). Many locations exhibit distinct seasonal cycles of fire activity driven by the annual march of weather, climate, and plant phenology—growing seasons that increase live fuel loads and dormant seasons that accumulate dead fuels—and the interplay of prolonged and short-term weather conditions producing receptive fuelbeds. Wildland fire events resulting from natural and human ignitions are influenced by longer-term climate conditions (i.e., seasonality and drought) but ultimately

require particular sequences of weather events to produce favorable fire environments (Schroeder and Buck 1970).

To link the seasonality of environmental conditions with fire danger for practical situational awareness, firefighters have utilized ‘Pocket Cards’ for over 20 years to provide historical and interpretive information such as local “watch out” conditions (Schlobohm (2000)). Developed by local fire managers, Pocket Cards provide quick references for key fire danger index values with historic fires and how indices change seasonally to improve firefighter safety (National Wildfire Coordinating Group 2026). The term ‘pyroclimograph’ arose when Swetnam et al. (2011) juxtaposed monthly mean temperature and precipitation with monthly burned area. Recent adaptations include monthly visualizations of historical mean as well as 10th and 90th percentiles to highlight years of interest (Sablan et al. 2024), and weekly-resolution plots separating prescribed burns from wildfires to reveal distinct fire-type seasonalities (Sweeney et al. 2025).

However, many wildland fires, especially prescribed burns (Hatchett and Wells 2026) or damaging wind-driven ‘fast fires’ (Balch et al. 2024; Hantson et al. 2022) may only burn for several hours or days. Aggregation of fire activity to monthly or even weekly timescales can obscure these daily-to-subdaily events and potentially allow conflation of short-term weather anomalies with climate if burning conditions deviate widely from climatology. A daily-resolution perspective that identifies receptive fire environments could support safer prescribed burn planning (Worsnop et al. 2026), regionally- and temporally-targeted messaging on prevention (Hesseln 2018; Abatzoglou et al. 2024) and preparedness (Abatzoglou et al. 2024; Hoekstra et al. 2026) as well as public education campaigns supporting smoke-readiness (D’Evelyn et al. 2023; Edgeley and Burnett 2025).

With over two decades of satellite-based fire detections, we can construct fire activity climatologies at daily resolution. These analyses can be tailored to user-defined regions meeting specific operational or planning needs. Regions can be defined by jurisdiction, (e.g., counties or National Weather Service (NWS) County Warning Areas (CWAs)), physical attributes (e.g., watersheds or mountain ranges; Snethlage et al. (2022b)), ecological attributes (e.g., ecoregions; Omernik and Griffith (2014)) or as relatively homogenous areas of contemporary fire regimes (e.g., pyromes; Short et al. (2020)). The proposed pyroclimograph approach offers a flexible visualization method to show daily wildland fire activity type and timing at decision-relevant scales to support operational fire management and emergency response (i.e., by augmenting Pocket Cards), longer-term planning for mitigation efforts, community outreach and education, and fire environment research.

Here, we demonstrate how to visualize pyroclimatology across three fire-prone regions using satellite-derived fire radiative power (*FRP*) and detection counts. We present four case studies showing how pyroclimographs: (1) illustrate distinct wildfire and prescribed burn seasonality, (2) track active fire seasons in near-real-time, (3) vary based on spatial region selected, and (4) integrate ancillary environmental information to isolate extreme fire environments. Finally, we use yearly rankings of annual total *FRP* to contextualize the unfolding 2026 season and evaluate how few, or how many days, drive overall fire activity in the satellite record.

2 Data

We downloaded post-processed 1-km horizontal resolution Moderate Resolution Imaging Spectroradiometer (MODIS) active fire detection data (counts and *FRP*; Giglio et al. 2016) spanning 1 January 2001–15 September 2026 using the MCD14DL product acquired from the NASA Fire Information for Resource Management System (<https://firms.modaps.eosdis.nasa.gov/>). MODIS overflights occur near 1030/2230 (Terra) and 0130/1330 (Aqua) local time, though in recent years orbital drift has increasingly delayed overpass timing on the order of hours.

To show pyroclimograph applications across varied geographic boundaries, we obtained county and state shapefiles from the U.S. Census Bureau (<https://www2.census.gov/geo/tiger/TIGER2025/>), NWS CWAs from the NWS County Warning Boundary Area Dataset (<https://www.weather.gov/gis/CWABounds>), and Environmental Protection Agency (EPA) Level III ecoregions from the EPA (<https://www.epa.gov/eco-research/level-iii-and-iv-ecoregions-continental-united-states>). We also used the pyrome delineations (areas of relatively homogenous fire activity) produced by Short et al. (2020). Finally, the Santa Monica Mountains boundary (a subrange of the Transverse Ranges excluding the Palos Verdes Hills) was acquired from the Global Mountain Biodiversity Assessment Mountain Inventory v2.0 (Snethlage et al. 2022a,b).

To demonstrate incorporation of fire environment data into a pyroclimograph, we extracted Energy Release Component (ERC; 1979–2025) from the daily, gridded ~ 4 km resolution gridMET product (Abatzoglou 2013) as a proxy for fire danger. To evaluate conditions driving ignition and spread, we acquired hourly 2 m relative humidity and 20 ft (6.1 m) wind speed and wind gust observations from the Western Regional Climate Center (<https://raws.dri.edu>) for the Malibu Hills, California Remote Automatic Weather Station (RAWS) spanning January 1995–February 2025.

3 Methods

We used MATLAB (The MathWorks Inc. 2024) to perform all analysis. Desiring maximum detectability, we retained all satellite detections regardless of processing algorithm-assigned confidence values (Giglio et al. 2016), acknowledging this may include occasional industry- or sun-glint-caused detections.

To visualize regional fire activity (Figures 1a,c), we let $s = \{s_1, \dots, s_n\} \in \mathcal{S}$ be the set of discrete detection pixels over some region $\mathcal{S}$ (e.g., United States) where s is indexed by longitude and latitude. Let $p_{i,j}(s) \geq 0$ be the *FRP* of pixel s on day i of year j . We define *FRP* over some user specified region $Reg \subseteq \mathcal{S}$ (e.g., *Reg* is a CWA, pyrome, or state) as

$$FRP_{i,j}(Reg) = \sum_{s \in Reg} p_{i,j}(s) \quad (1)$$

The cumulative annual *FRP* up to calendar day k of year j , denoted $C_{k,j}(Reg)$, is defined as:

$$C_{k,j}(Reg) = \sum_{i=1}^k FRP_{i,j}(Reg) \quad (2)$$

where $k \in \{1, 2, \dots, K_j\}$ is the calendar day index of year j up to $K_j = 365$ or $K_j = 366$. To show the seasonality of fire activity timing within a region, counts of total daily detections across all years are binned by calendar day (Figures 1b,d, 2, and 3a). In these figures, notable years and/or fires are highlighted.

To extend pyroclimographs into a Pocket Card format incorporating fire danger and fire activity seasonality (Figure 3), we extracted mean ERCs from gridMET using a bounding box encompassing the Santa Monica Mountains (Figure 3b). Daily percentile values commonly used in operational ERC plots and Pocket Cards (including the 3rd, 20th, 50th, 80th, 97th and 100th) were calculated between 1979–2025 and smoothed with a 5-day running mean (shaded regions in Figure 3b). Following operational ERC climatologies, annual 50th, 90th, and 97th ERC percentiles were calculated using all days (denoted by dashed horizontal lines in Figure 3b). We used the Malibu Hills RAWs to calculate fire weather hours (Figure 3c) as the to number of hours each calendar day spanning 1995–2025 that meet either of two established Red Flag Warning (RFW) criteria in the Santa Monica Mountains (California Annual Operating Plan 2026). The first RFW criteria is characterized as “dry but with less wind”. This criteria requires relative humidity $\leq 10\%$ with either a sustained wind speed $\geq 6.7 \text{ m s}^{-1}$ ($\geq 15 \text{ miles hr}^{-1}$) or wind gusts $\geq 11.2 \text{ m s}^{-1}$ ($\geq 25 \text{ miles hr}^{-1}$). A second RFW criteria requires less dry conditions but greater winds. Here, RFW criteria include relative humidity $\leq 15\%$ with sustained wind speed $\geq 11.2 \text{ m s}^{-1}$ ($\geq 25 \text{ miles hr}^{-1}$) or gusts $\geq 15.6 \text{ m s}^{-1}$ ($\geq 35 \text{ miles hr}^{-1}$). In both cases, if these conditions are sustained for over six hours with critically dry fuels, a RFW may be issued.

To rank 2026 against other years, we let $S_j(Reg) = C_{K_j,j}(Reg)$ represent the cumulative *FRP* from 1 January through 31 December (or 15 September in the case of 2026) for year $j \in \mathcal{Y}$. Here, $\mathcal{Y} = \{2001, 2002, \dots, 2026\}$ is the set of all years in the satellite record ($N_y = 26$). We define the ranking of 2026 within region *Reg* as $\text{Rank}_{2026}(Reg)$:

$$\text{Rank}_{2026}(Reg) = |\{j \in \mathcal{Y} \mid S_j(Reg) \geq S_{2026}(Reg)\}| \quad (3)$$

where $|\cdot|$ denotes the cardinality of the set of years such that $\text{Rank}_{2026}(Reg) = 1$ indicates 2026 is the record-high *FRP* year (Figure 4).

To quantify the number of days contributing to total *FRP* (*tFRP*; the temporal concentration of fire activity; Figure 5a–c) within a pyrome, we calculate the minimum number of days needed to contribute a given fraction (or percent) of *tFRP*. We let $\mathbf{y} = (y_1, y_2, \dots, y_N)$ be the vector obtained by sorting all daily regional $FRP_{i,j}$ entries across the record in descending order, such that $y_1 \geq y_2 \geq \dots \geq y_N$, where $N = 9,389$ total days. The cumulative sum of the most active (top κ) days is $C_\kappa = \sum_{m=1}^{\kappa} y_m$, and $tFRP = C_N = \sum_{m=1}^N y_m$. The minimum number of days κ_P^* required to achieve P percent of *tFRP* is identified by:

$$\kappa_P^* = \min \{\kappa \in \{1, 2, \dots, N\} \mid C_\kappa / tFRP \times 100\% \geq P\} \quad (4)$$

The corresponding fraction of total days contributing to P percent of days is given by $f_P = \kappa_P^* / N$ (Figure 5d).

174 4 Results

175 4.1 Pyroclimographs: First-Order Applications

176 Colusa County, California—a rural agricultural community composed of forest, oak
177 savannah rangelands, and arable crops—demonstrates three distinct burn seasons
178 within a calendar year: small increases in annual cumulative *FRP* during mid-winter
179 to spring (mid-January–April), rare but high-*FRP* events during the extended sum-
180 mer (late June–September), and a shift back to gradual, annually consistent increases
181 during fall (October–November; Figure 1a). Cross-referencing county-level prescribed
182 burn permit data (Worsnop et al. 2026) and CAL FIRE fire history data ([https://](https://www2.fire.ca.gov/what-we-do/fire-resource-assessment-program)
183 www2.fire.ca.gov/what-we-do/fire-resource-assessment-program), the consistent daily
184 detections with lower *FRP* (Figure 1b) indicate that planned agricultural and pre-
185 scribed burning dominate during spring and fall. This contrasts with notably higher
186 *FRP* and increased detection counts associated with summer wildfire incidents in
187 2012, 2018, and 2024 (labeled in Figure 1b).

188 Wildland fire activity occurs year-round in the NWS Norman (OUN)-NWS Amar-
189 illo (AMA) region of the U.S. Southern Great Plains (Figures 1c,d). Following the dry
190 winter season, fire activity peaks in March–April (Lindley et al. 2019) and declines with
191 the onset of late-spring convective precipitation that initiates green-up of herbaceous
192 and grass fuels. Rapid satellite fire detections availability allows pyroclimographs to
193 track the progression of a fire year in near-real-time. For example, persistent drought
194 and heavy fine fuel loading primed the fire environment for dry and windy weather to
195 initiate the 2026 wildfire season approximately two weeks early (red line in Figure 1c).
196 Because planned and unplanned ignitions overlap seasonally in the OUN-AMA region,
197 separating ignition types in a climatological sense or for individual years (Figure 1d) is
198 challenging without incorporating agency records. Although annual cumulative *FRP*
199 curves (Figures 1a,c) facilitate interannual comparisons, e.g., identifying early onset of
200 2026 fire activity, we focus primarily on daily detection bar charts (e.g., Figures 1b,d)
201 in Sections 4.2 and 4.3.

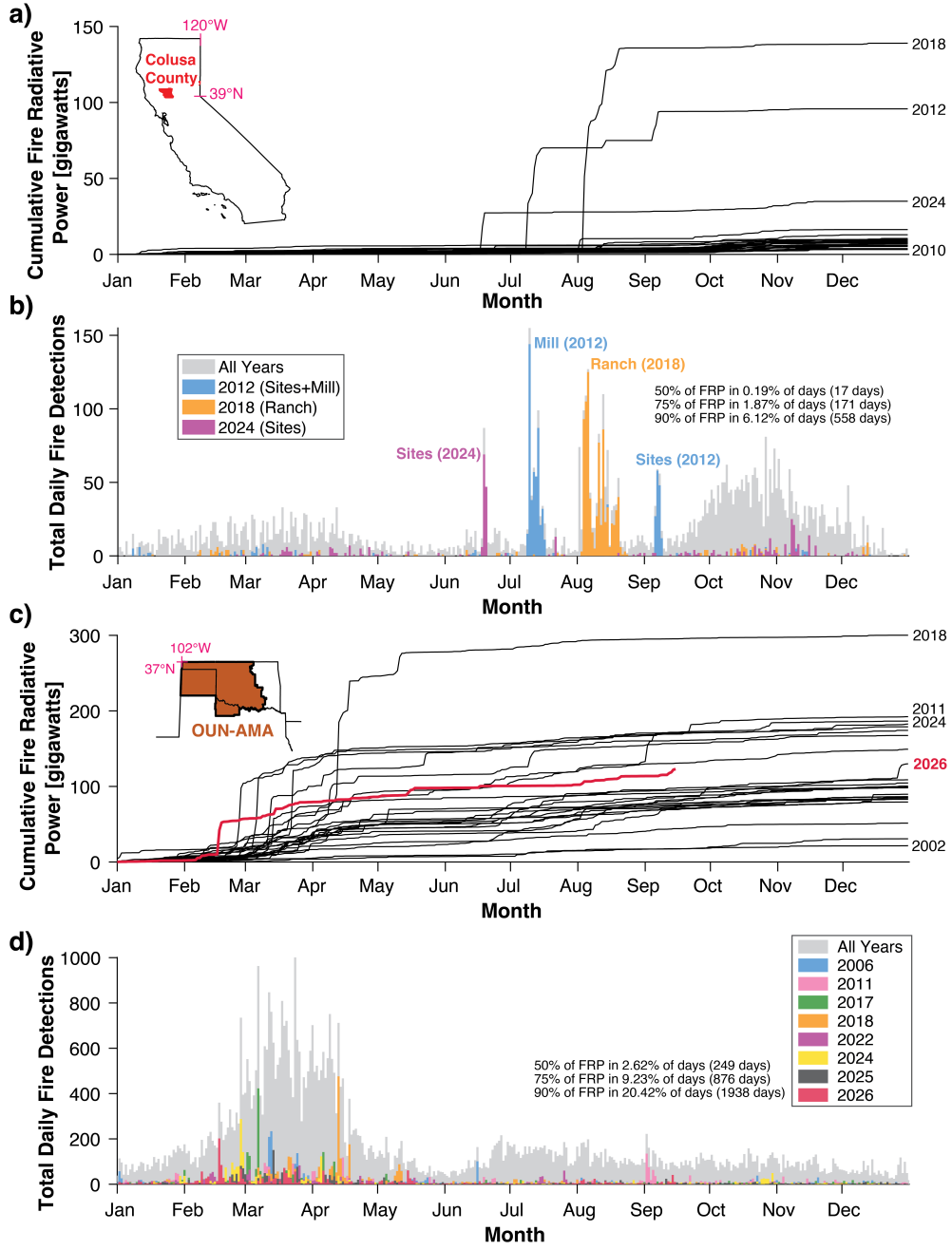


Fig. 1 (a) Pyroclimograph showing daily cumulative FRP ($C_{k,j}$) in Equation 2) for each calendar year (2001–2025; highest three and lowest year labeled) for Colusa County, California. (b) Period-of-record total daily fire detections across years (gray bars). Contributions from notable fire years are colored, with specific fires labeled. (c,d) As in (a,b) but for the Norman, Oklahoma (OUN) and Amarillo, Texas (AMA) NWS CWAs (bold red line shows 2026 through 15 September) with notable fire years labeled (see e.g., Lindley et al. 2019).

4.2 Pyroclimograph Sensitivity to Domain Selection: An Example in Coastal Southern California

Here, we explore how pyroclimographs clarify fire history interpretation across different regional domains. The Southern California Mountains/Northern Baja pyrome (largest region) spans interior Santa Barbara County south to San Diego County (Figure 2a). This pyrome experiences its largest and most destructive wildfires between May and early January. However, consistent cool-season detections with low *FRP* indicate potential cool-season prescribed burning. Two EPA Level III Ecoregions comprise this pyrome. In the higher-elevation Southern California Mountains ecoregion—composed of mixed shrubland, grassland, and forest vegetation—the pyroclimograph shows fire activity typically spans June to mid-October (Figure 2b). Warm-season wildfires tend to be fuel- and terrain-dominated. Cool-season wildfires result from dry downslope Santa Ana wind events. These cause the most damage to life and property (Syphard et al. 2021) when winds precede season-ending precipitation (Cayan et al. 2022; Guirguis et al. 2025).

The lower elevation, chaparral and coast sage and chaparral-dominated Southern California Coast/Northern Baja ecoregion experiences fewer fires in the summer (Figure 2; the 2018 Holy Fire is an exception) due to higher summer live fuel moisture (c.f. supporting information in Guirguis et al. 2025). Fire activity peaks in the late fall to early winter due to human-ignited fires, often during Santa Ana wind events (Figure 2c). The NWS Los Angeles CWA (Figure 2d) includes more interior dry regions (e.g., where the 2025 Madre and Gifford Fires occurred) and elevated terrain susceptible to both human and lightning ignitions. Hotter and drier conditions yield an extended fire activity window spanning May through early January, with a pronounced peak between July and September when large-scale downslope winds are typically absent. Heavy, contiguous fuels and steep topography sustain active fire behavior, especially when alignment of both local terrain-driven and general winds occurs.

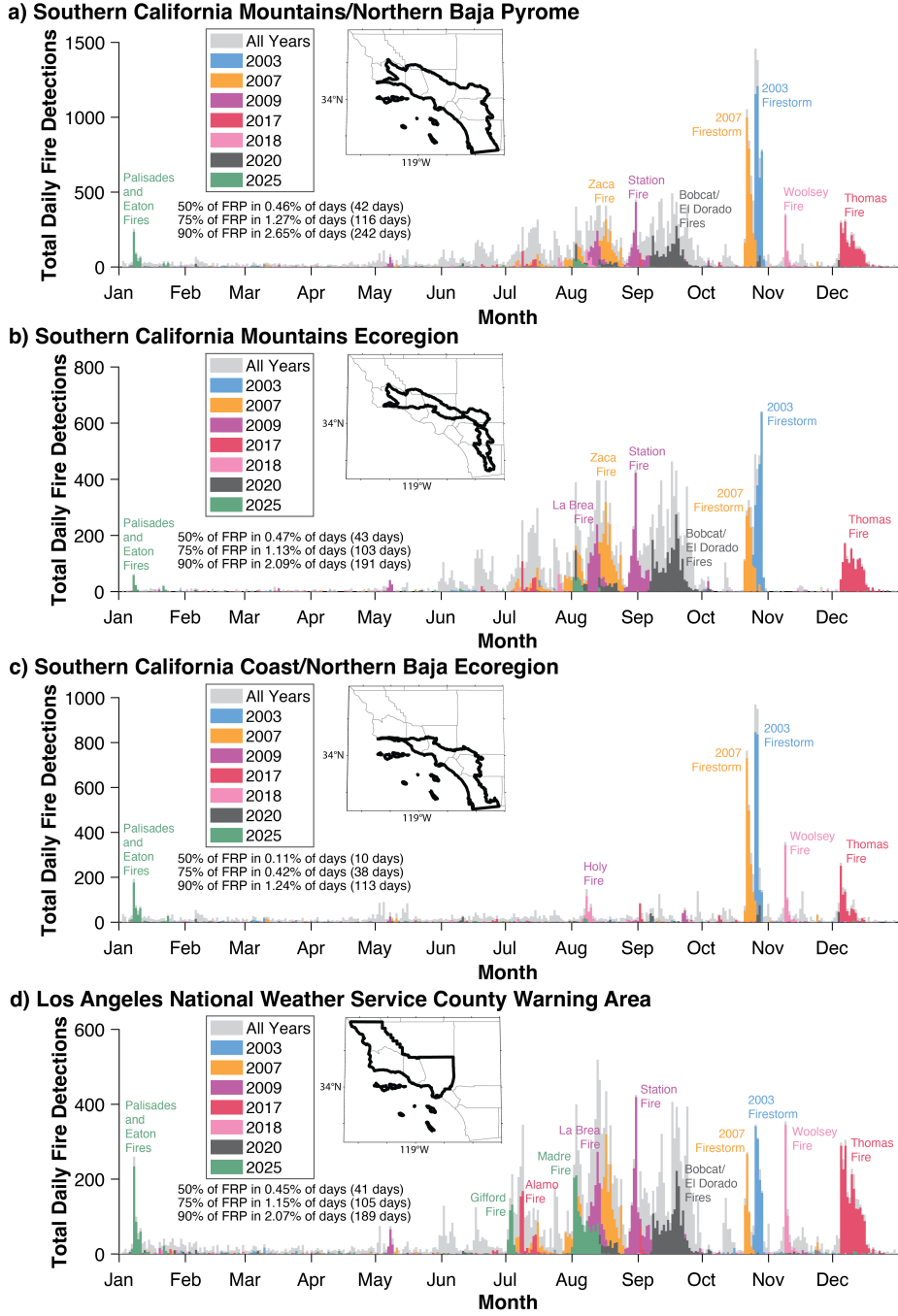


Fig. 2 Pyroclimographs illustrating fire activity across different spatial delineations in coastal Southern California: (a) Southern California Mountains/Northern Baja pyrome, (b) EPA Level III Southern California Mountains ecoregion, (c) EPA Level III Southern California Coast/Northern Baja ecoregion, and (d) NWS Los Angeles CWA. Total daily fire detections spanning 2001–2025 are shown by gray bars with notable historical fires labeled. The inset text explains the number of days (k_P^* ; recall Equation 4) required to achieve 50%, 75%, and 90% of total record FRP ($tFRP$).

4.3 Towards a More Complete Pyroclimograph

Our motivation to extend the monthly-scale pyroclimograph proposed by Swetnam et al. (2011) is to provide a more complete picture of fire activity and the fire environment at daily timescales. This information can then be formatted similarly to Pocket Cards (Schlobohm 2000), where satellite-derived daily fire history, ERC, and Burning Index are displayed together. The Santa Monica Mountains of Ventura and Los Angeles Counties represent an ideal location to demonstrate how daily fire weather deviates from climatological conditions. As Section 4.2 noted, low relative humidity and strong offshore downslope Santa Ana winds occurring before season-ending rainfall enable extreme fire behavior in coastal Southern California. Fire is infrequent but highly impactful, as illustrated by the result showing 90% of total record *FRP* (*tFRP*) was achieved in just 10 fire days during 2001–2025 ($k_{90\%}^* = 10$; Figure 3a). The number of days contributing to a given fraction of *tFRP* increases with domain size, with 113–242 days ($k_{90\%}^*$) required across larger coastal Southern California regions (Figure 2). Elsewhere, many days ($k_{90\%}^* = 1,906$ days in the OUN-AMA region; Figure 1d) are required to reach 90% of *tFRP*, collectively illustrating regional and domain-dependent differences in fire activity concentration.

Merging fire detection and ERC climatologies modernizes the pocket card concept by linking full fire climatologies (Figure 3a) for concurrent comparison with daily and annual ERC percentiles (Figure 3b) rather than static annual summaries. Mountain range-mean ERC on the ignition dates of notable Santa Monica Mountains fires (including the 2017 Thomas Fire and 2024 Mountain Fire which were nearby high-impact fires) indicates the timing of major fires is typically between October and January. An exception is the 2013 Springs Fire that ignited during a spring wind event under moderate drought conditions per the U.S. Drought Monitor (Svoboda et al. 2002). All eight fires ignited on days with above-median ERCs; however, only the Palisades Fire ignited above the annual 90th percentile.

To compare critical weather drivers with the pyroclimograph, we evaluated fire-weather hours in the Santa Monica Mountains meeting RFW criteria for relative humidity and wind speed (omitting the wind duration constraint). Seasonally, fire-weather hours are infrequent from late May–September, increase in frequency during October–November, peak in December–January, and decline through May (Figure 3c). As noted in Section 4.2, problematic fire occurrence closely relates to live fuel moisture (Dennison and Moritz 2009), which reaches its annual minimum by September–October before recovering in December (Guirguis et al. 2025). Like Pocket Cards, merging additional fire weather data with pyroclimographs reflects the juxtaposition of factors contributing to Santa Monica Mountain fire activity: critically dry fuels, strong dry winds, and an ignition source.

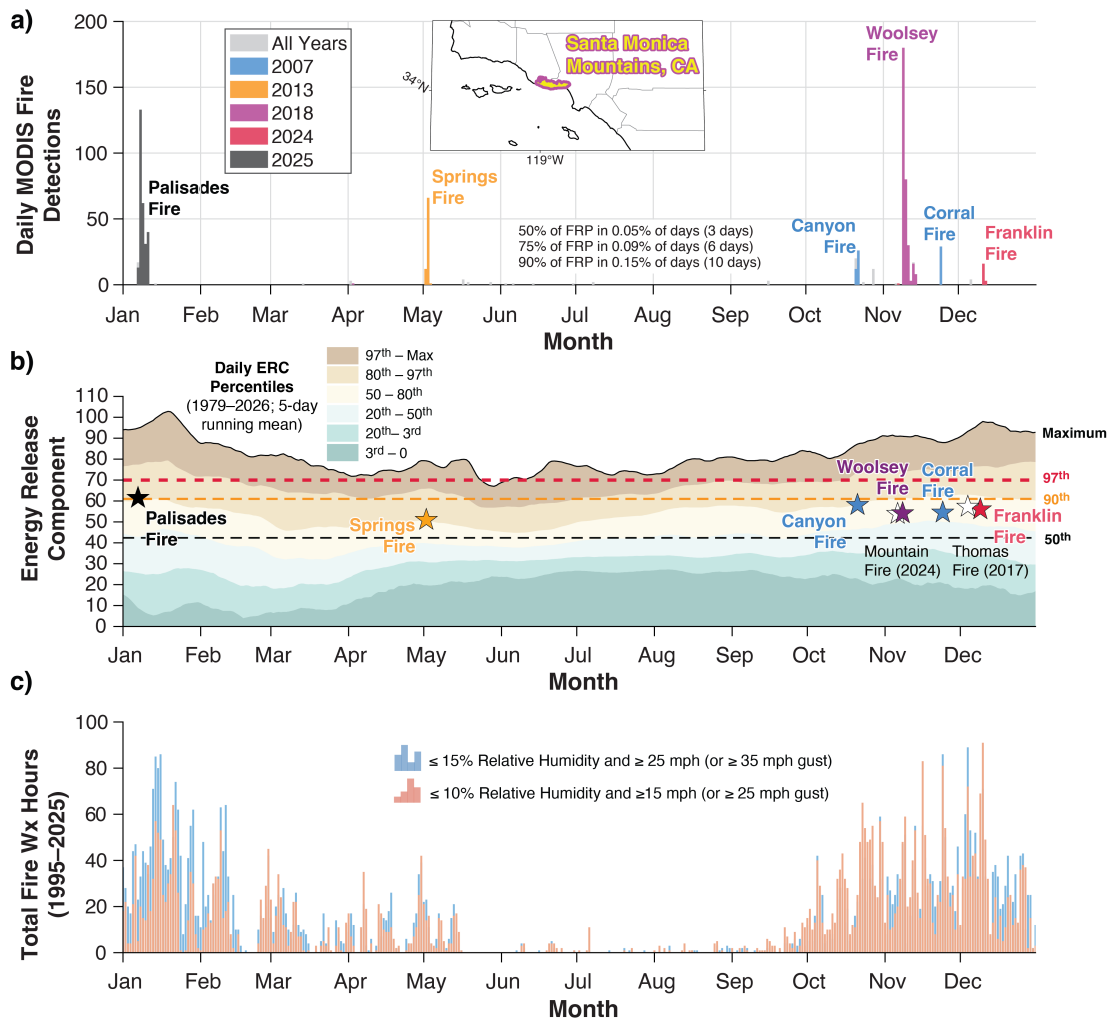


Fig. 3 (a) Pyroclimograph showing period-of-record total daily fire detections (gray bars; left y-axis) for the Santa Monica Mountains of Southern California (inset map), with contributions from notable named fires colored by year. (b) Daily Energy Release Component (ERC) climatology with shaded regions representing daily percentile bins (3rd, 20th, 50th, 80th, 97th, and 100th) and horizontal dashed lines marking all-time percentiles (50th, 90th, and 97th). Domain-mean ERC values on the day of ignition are plotted for notable local fires, along with two nearby damaging events (2017 Thomas Fire and 2024 Mountain Fire). (c) Total daily fire-weather hours spanning January 1995–February 2025, calculated using NWS RFW criteria for wind speed and relative humidity at the Malibu Hills RAWS.

4.4 A Pyroclimatological Perspective of 2026

Pyroclimographs produced at the NWS CWA, pyrome, and state level indicate widespread anomalous fire activity during 2026 (through 15 September). To complement pyroclimographs and add a spatial component to the near-real-time tracking,

272 Figure 4 demonstrates the ranking of $tFRP$ for 2026 cumulative FRP ($S_{2026}(Reg)$)
 273 relative to full calendar years spanning 2001–2025 across the three spatial delineations
 274 ($Rank_{2026}(Reg)$; Equation 3). Multiple regions across the U.S. experienced record or
 275 near-record high fire activity in 2026. Five of 117 NWS CWAs recorded their high-
 276 est total annual FRP on record, with 20 ranking in the top five (Figure 4a) while
 277 seven of 136 pyromes recorded their highest FRP , with 25 in the top five (Figure 4b).
 278 One of 50 states (Utah) set a record high, with six states ranking in the top five
 279 (Figure 4c). Conversely, many areas experienced record low fire activity through 15
 280 September, including 19 CWAs (55 ranking in the bottom five years), 21 pyromes (48
 281 in the bottom five years), and 11 states (24 in the lowest five years).

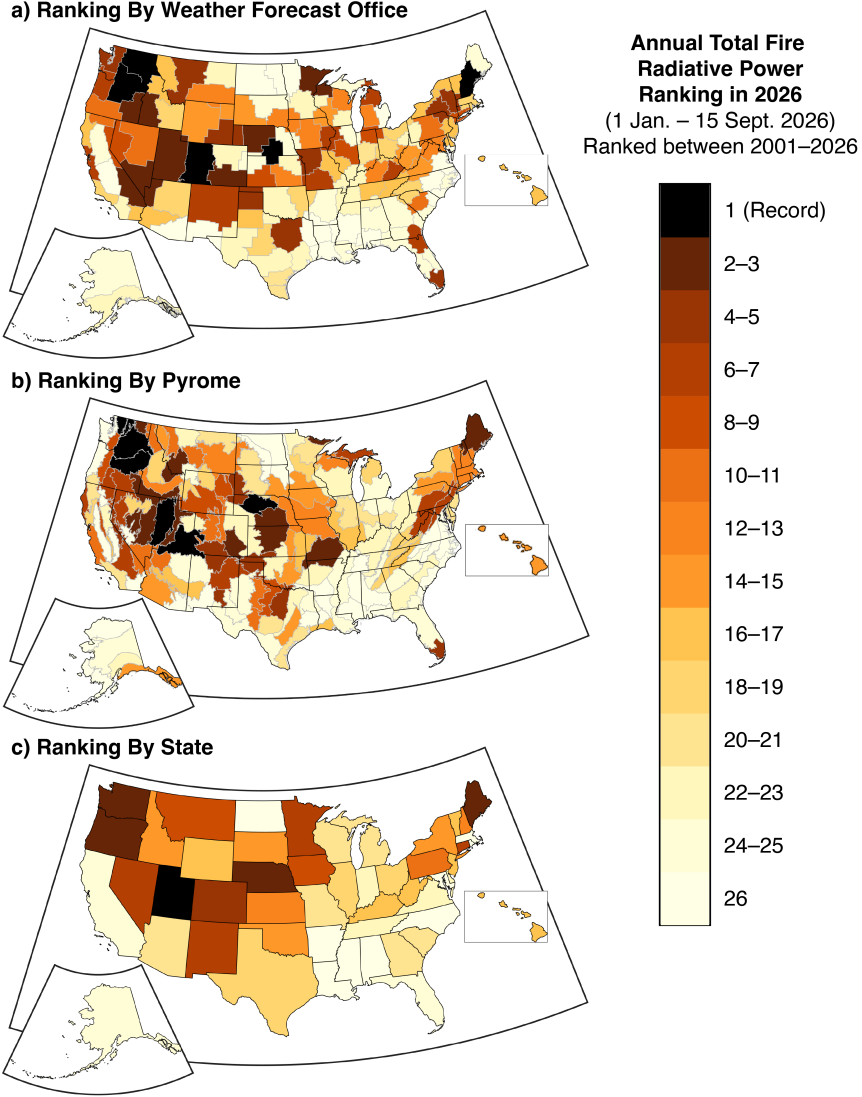


Fig. 4 Ranking of cumulative fire radiative power observed between 1 January–15 September 2026 ($\text{Rank}_{2026}(\text{Reg})$) against complete calendar years (2001–2025) by (a) NWS CWA, (b) pyrome, and (c) state.

4.5 Temporal Concentration of Fire Activity

The variation in k_P^* across our case studies highlights a central question in climatology: do a few extreme events or many commonplace events drive the signal? Figures 5a–c indicate spatial variability in k_P^* , the minimum number of fire activity days required to produce a given fraction P of total record FRP ($tFRP$) across pyromes. Achieving 20% of $tFRP$ requires relatively few days ($k_{20\%}^* < 5$ days) across 46 pyromes spanning

288 the interior West, northern Midwest, northern Rockies, and Alaska compared to over
 289 100 days in 10 pyromes across the Southeast, Midwest, and in California’s Central
 290 Valley (Figure 5a). A similar spatial pattern holds for 50% ($k_{50\%}^*$; Figure 5b), with
 291 37 pyromes requiring $k_{50\%}^* < 20$ days and 34 pyromes requiring $k_{50\%}^* > 200$ days.
 292 The Great Basin, Rocky Mountains, northern Great Lakes, West Texas, and parts of
 293 Alaska require factors of 10–50 fewer days to accumulate 90% of $tFRP$ than regions
 294 experiencing frequent, lower-intensity burning such as the Southeast, Great Plains, and
 295 Ohio River Valley (Figure 5c). At this threshold, 35 pyromes required $k_{90\%}^* < 184$ ($< 2\%$) days and 30 required $k_{90\%}^* > 1,408$ ($> 15\%$) days. The five pyromes with the
 296 least and most extreme $k_{90\%}^*$ were < 57 and $> 2,726$ days, respectively.
 297

298 Across all $tFRP$ thresholds (10%–90%), the number of required days varies by
 299 pyrome (Figure 5d), consistent with the map results. Throughout the western U.S.,
 300 relatively few high FRP days—likely rare multi-day wildfire incidents (Figure 1b and
 301 Figure 2)—dominate $tFRP$. In contrast, the Southeast and California’s Central Valley
 302 require 10–80 times more days to reach equivalent $tFRP$ fractions, demonstrating
 303 regimes characterized by frequent, lower-intensity fire activity rather than rare, quasi-
 304 episodic (occurring within a typical seasonal window, but not every year), higher-
 305 intensity and larger wildfires.

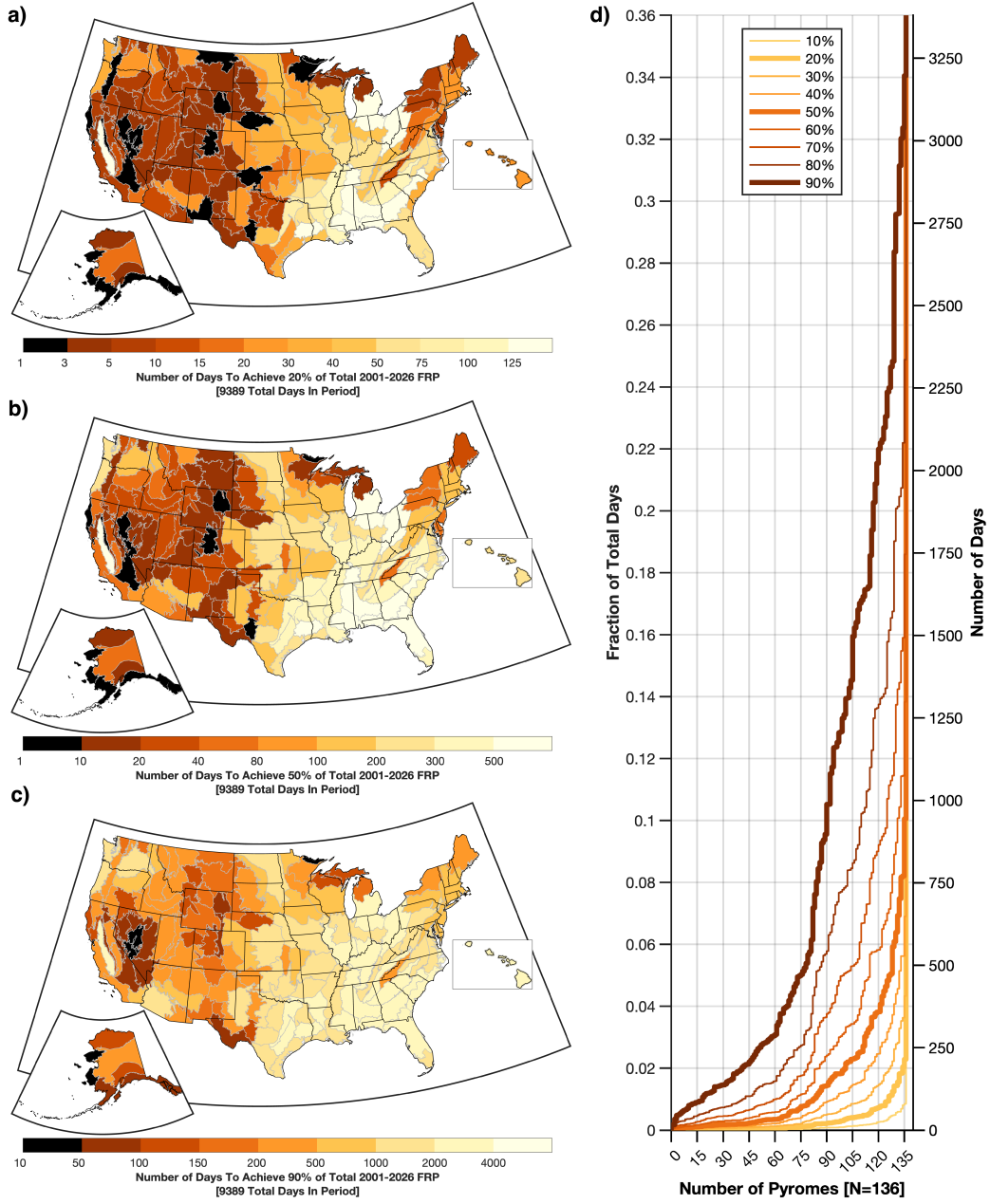


Fig. 5 Number of days by pyrome (k_P^*) required to achieve (a) 20%, (b) 50%, and (c) 90% of total 2001–2026 Fire Radiative Power ($tFRP$, evaluated through 15 September 2026). (d) Cumulative number of pyromes achieving specified fractions of $tFRP$ versus the fraction of total record days (f_P left y-axis) and actual number of days (right y-axis). Bold lines indicate the 20%, 50%, and 90% $tFRP$ thresholds shown in (a–c).

5 Discussion

Daily, satellite-based pyroclimographs offer more temporal granularity and spatial flexibility than traditional fire perimeters that record only discovery and containment dates (Swetnam et al. 2011; U.S. Geological Survey and U.S. Department of Agriculture Forest Service 2025) or weekly-to-monthly aggregations of satellite-based detections (Giglio et al. 2009; Abatzoglou et al. 2023; Sablan et al. 2024). When cross-referenced with agency management records (Sweeney et al. 2025; Worsnop et al. 2026), persistent low-*FRP* detections can help resolve local-to-regional prescribed or agricultural burn seasonality and help identify ideal burn windows when merged with weather and fuels conditions (Worsnop et al. 2026). Pyroclimographs thus can serve versatile roles in operations and training: educating staff and the public on regional fire history, identifying windows for beneficial fire, contrasting fuel- versus wind-driven regimes, and tracking a year’s evolution against climatological norms in near-real-time. Other historical datasets (St. Denis et al. 2020) could also be incorporated to extend the pyroclimographs into the pre-satellite era.

By quantifying instantaneous fire energy across an area during satellite overpass, *FRP* is a key input to atmospheric smoke transport models (Ahmadov et al. 2017). Anomalous *FRP* values act as a first-order proxy (bearing in mind the limitations of satellite fire detections) for potential downstream air quality, public health, and economic impacts, thereby extending the potential utility of pyroclimographs as an integrated measure of impacts extending beyond conventional area-burned or burn severity metrics.

The spatial distribution of the 2026 rankings (Figure 4) illustrates how spatial scale influences the interpretation of fire activity and implies careful analysis is necessary to understand the representativeness of events across scales as aggregation to state levels may mask localized, high-impact events. Georgia provides an example. A period of active wildfire in spring 2026 included the Highway 82 Fire, which destroyed 110 structures; the most in state history (Carney 2026) and the Pineland Road Fire. While these fires led to a top-five ranking at the CWA level (Figure 4a), the annual pyrome- and state-level rankings were in the bottom five years (Figure 4c). Florida had a similar result, with top five activity at the CWA and pyrome-levels but bottom five activity at the state-level. Conversely, localized fire activity can dominate broader regional signals. In Minnesota, active burning in the Boundary Lakes and Hills pyrome in 2026 (Figure 4b) produced a top-two CWA ranking and a top-five state-level ranking.

Evaluating the temporal concentration of fire activity (k_P^*) at the pyrome level yields a parallel to hydroclimatology. In contrast to many regions in the U.S., a small number of storms associated with atmospheric rivers largely contribute (upwards of 50%) to total annual precipitation and account for over 80% of interannual variability in California (Dettinger et al. 2011). We observe a similar pattern in fire regimes (Figure 5): many pyromes, especially in the western and central U.S. are dominated by a handful of rare, high-intensity wildfire days. This aligns with findings that the vast majority of damaging ‘fast fires’ (Balch et al. 2024) and large fractions of smoke emissions (Urbanski et al. 2018) occur during extreme (i.e., rare) fire environments.

Re-framing fire activity through a temporal concentration lens may address the “wildfire paradox” (Calkin et al. 2014). Communicating that low fire frequency results

from fire exclusion and yields less frequent, but catastrophic wildfire and that more frequent fire of the right intensity and producing the desired fire effects is needed (with communities prepared to receive fire) may help build public support for beneficial fire through improved understanding of regional fire ecology.

Beyond annual counts, pairing pyroclimographs with cumulative *FRP* rankings provides a framework for ongoing and post-fire season evaluation and decision support. Identifying regions that experienced anomalously high fire activity informs where after-action reviews of public messaging and decision support to partners may benefit agencies. For example, evaluating NWS Weather Forecast Office and state-level messaging before and during fire events could both support improving messaging and serve as training opportunities for early career staff. At the seasonal scale, cumulative *FRP* rankings offer a potential quantitative metric to evaluate the skill of operational outlooks, such as Predictive Services' Significant Wildland Fire Potential Outlooks (<https://www.nifc.gov/nicc/predictive-services/outlooks>).

Satellite-based pyroclimographs generally visualize a minimum amount of fire activity, with a key limitation stemming from observation timing. Polar-orbiting satellites provide discrete snapshots, capturing a lower bound of fire activity while missing fire spread between overpasses and low-intensity fires. However, false positives in industrialized areas or adjacent to pyroconvective plumes and volcanic activity (Hawaii) requires additional investigation to avoid over-counting. In the case of Hawaii, differing spatial definitions produced a higher rank in 2026 (Figure 5), as the pyrome shapefile included a buffer that captured more detections. A challenge for data continuity awaits as MODIS approaches decommissioning in 2027. Continuation of pyroclimographs will require harmonizing MODIS and VIIRS active fire records as VIIRS becomes the primary detection source. Expanding pyroclimographs to integrate high-frequency geostationary observations (e.g., 5-minute data from the Geostationary Operational Environmental Satellite Advanced Baseline Imager) and newly-launched missions like FireSat (<https://sites.research.google/gr/wildfires/firesat/>) will improve temporal and spatial resolution. We expect multi-sensor fusion to yield more robust fire histories by improving estimates of fire rates-of-spread and environmental conditions at the time of burning, as well as supporting model verification and interpretations of postfire burn severity (Orland et al. 2025).

Relying solely on climatological means in pyroclimographs (Swetnam et al. 2011) likely masks weather anomalies enabling fire activity or extreme fire behavior. Drivers of the fire environment operate across interconnected but also independent timescales including intraseasonal weather variability (e.g., heatwaves, downslope wind events, wet and dry spells) to interseasonal wind (e.g., Santa Ana Winds) or precipitation patterns (e.g., convective or frontal precipitation or seasonal drought) and interannual-multidecadal climate variability (pluvials and drought). The metrics we used in Southern California such as domain-mean ERC and fire-weather hours therefore serve as first-order proxies. Future iterations of pyroclimographs will extract co-located fire environment conditions at exact overflight times to better evaluate driving states and mechanisms during rapid fire growth, verify weather and fire behavior models, and clarify how environmental states across timescales influence outcomes such as burn severity (Orland et al. 2025).

6 Conclusions

We revisited the concept of pyroclimographs by leveraging satellite fire detections to explore a facet of pyrogeography: linking the “where of fire when” to understand “the why of fire.” By providing a daily-resolution perspective, pyroclimographs contextualize a region’s satellite-era fire activity and clarify fire history, especially when complemented with fire environment data. We found pyroclimographs able to visually characterize periods of fire absence, frequent lower-*FRP* activity indicating prescribed burning or lower-intensity wildfire, and rare, high-*FRP* events that indicate wildfires. By additionally incorporating the seasonal variation of fire danger metrics such as ERCs or environmental metrics like fire weather hours, pyroclimographs mimic Pocket Cards and better demonstrate why general or notable fire activity occurs (or does not) during particular windows of time. The intentional simplicity of pyroclimographs aims to maximize their utility to scientific research, agency tracking, public outreach, and operational situational awareness and training.

Declarations

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- Data availability: Processed MODIS data and pyroclimographs for each CWA, pyrome, and state are available via Zenodo (Hatchett 2026).
- Code availability: MATLAB code to produce pyroclimographs is available on GitHub: <https://github.com/213blc/MESSci/tree/main/pyroclimographs>.
- Declaration of AI technology use: During the preparation of this work, BJH used Gemini to help formalize equations describing methods and to ensure consistent $\LaTeX$ formatting. After using this tool, authors BJH and JSN reviewed and edited the content. BJH takes full responsibility for the content of the publication.
- Author contributions: BJH conceptualized the project, wrote the original draft, performed the analysis, and prepared the figures. All authors contributed to improving the conceptualization, performing the investigation and the review and editing of the manuscript.

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