CALIFORNIA
AIR RESOURCES BOARD

Technical Documentation of the Emissions Inventory of Vegetations Burned in Wildfires

Technical Supplement: Method Performance Analysis, Discussion, and Supplementary Figures & Tables

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October 2025

Acknowledgements

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CARB staff wish to express their appreciation to many individuals and organizations that were an integral part of developing the daily wildfire perimeter and emissions inventory. We would like to thank the following for providing their technical and scientific support:

National Aeronautics and Space Administration and University of Maryland
- Tempest McCabe, Ph.D.
- Elijah Orland
- Zebediah Becker
- Douglas Morton, Ph.D.
- Melanie Cook, Ph.D.

Development Seed
- Greg Corradini

Element 84
- Julia Signell

University of California, Irvine
- Yang Chen, Ph.D.

University of California, Davis
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California Department of Forestry & Fire Protection

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S-1: Method Performance Analysis

I. Perimeters

The accuracy of fire perimeters predicted by Fire Events Data Suite (FEDS, Chen *et al.* 2022) affects the precision of emission estimates. FEDS perimeters are evaluated by comparing the final fire sizes to those from CAL FIRE perimeters (*https://www.fire.ca.gov/what-we-do/fire-resource-assessment-program/fire-perimeters*) using linear regression. To assess the spatial alignment between FEDS and CAL FIRE perimeters, a suite of metrics measure both accuracy and overlap: F1 score, Intersection over Union (IoU), user's accuracy, and producer's accuracy (Fig. 3). These metrics offer insights into the precision of predictions, the extent of agreement between datasets, and the balance between false positives and false negatives.

To assess the factors influencing FEDS performance, IoU values are modeled using a Bayesian beta regression model. IoU is prioritized over the F1 score because IoU is more sensitive to extreme cases, especially when the true positive area is small. This heightened sensitivity to poor spatial matching better identifies predictions with significant errors, making IoU a more conservative metric for evaluating overall model performance. Models incorporating predictive variables, such as vegetation composition, fire duration, and fire size, were compared using leave-one-out cross-validation. Continuous variables were centered and standardized by dividing by 2 standard deviations (Gelman, 2008). The model with the best predictive performance, as indicated by difference in expected log predictive density (ELPD) was selected (Vehtari *et al.* 2017).

Since FEDS data is inherently temporal, the accuracy of perimeters was assessed over time by comparing them to aerial infrared (IR) perimeters. Aerial data were obtained from the National Interagency Fire Center File Transfer Protocol website (*https://ftp.wildfire.gov/public/incident_specific_data/*) and manually cleaned and standardized. The spatial alignment between FEDS and aerial IR perimeters were evaluated using the same suite of metrics—F1 score, IoU, user's accuracy, and producer's accuracy. For the fires with aerial IR data, relative cumulative growth rates were compared across four sources: FEDS perimeters, aerial IR perimeters, growth rates reported in the US EPA National Emissions Inventory (NEI, *https://www.epa.gov/air-emissions-inventories/get-air-emissions-data-0*), and estimates based on fractional daily counts from Visible Infrared Imaging Radiometer Suite (VIIRS). This last approach mirrors recent methods used by CARB for the 2024 San Joaquin Valley PM 2.5 SIP (San Joaquin Valley Air Pollution Control District 2024), which temporally partitioned total bulk emissions from fires across multiple days using VIIRS active fire product (AFP). To evaluate the agreement between predicted and observed daily fire growth, root mean square error (RMSE) was calculated between aerial IR growth rates (treated as reference) and those derived from FEDS, the NEI, and VIIRS-based counts. RMSE values were computed separately for each fire and then compared across sources using ANOVA on log-transformed RMSE values (transformed to approximate a gaussian distribution), along with Tukey's post-hoc test to determine significant pairwise differences.

II. Emissions

The primary goal of this inventory is to accurately track wildfire emissions. Unlike fire perimeters, which can be directly validated by comparing predictions to ground-truthed sources (e.g. CAL FIRE and aerial IR perimeters), emissions are typically measured at monitoring stations, which present unique challenges in tracing wildfire smoke back to its source. Once smoke rises into the atmosphere, it disperses stochastically, influenced by factors such as topography, atmospheric pressure, and wind patterns (Goodrick *et al.* 2013). Additionally, the pollutants measured by monitoring stations can originate from a myriad of sources, such as multiple fires and other natural and anthropogenic sources, making it difficult to isolate emissions from a single fire. Because of this complexity, it is out of scope of this report to validate wildfire emissions against air monitoring station data. Nonetheless, CARB compares results to other inventories and examines how they differ.

The impact of the most significant change to the inventory methodology—inclusion of daily FEDS perimeters—is evaluated by comparing $PM_{2.5}$ emissions (representing the sum of the flaming and smoldering phases) derived from FEDS perimeters to those from CAL FIRE perimeters. The CAL FIRE-based emissions act as a proxy for the previous CARB inventory approach, as they yield total bulk emissions rather than daily emissions and use the same perimeters as before. To enable a direct comparison, daily FEDS-based emissions were summed by fire to produce total bulk estimates, and a linear regression was conducted to compare these totals against those derived from CAL FIRE perimeters.

To benchmark the updated inventory against other relevant inventories, estimates were compared against CARB's past wildfire emissions inventory and the NEI. The past CARB inventory removed emissions and acres burned from agricultural and non-vegetated land to capture effects from burned wildland vegetation, whereas the current inventory does not omit any land types. To directly contrast inventories, agricultural and non-vegetated land were removed from the current inventory just for this comparison. $PM_{2.5}$ data were available across all three inventories, while CO_2 and acres burned were available for just the CARB inventories. Both $PM_{2.5}$ and CO_2 represent the sum of emissions from the flaming and residual smoldering phases. These comparisons offer insight into consistency, divergence, and potential areas for further refinement.

III. Data processing and analysis

The modified FEDS data pipeline was developed in `Python` ver. 3.11 (Python Software Foundation 2022) and builds upon the `fireatlas` package maintained by the NASA and University of California, Irvine team (*https://github.com/Earth-Information-System/fireatlas*). The pipeline that estimates emissions and consumption in FOFEM was also implemented in

Python and compiled into a package called `pyfofem`, which is available upon request from CARB. Packages `geopandas`, `xarray`, and `shapely` were used for spatial analyses (Gillies & others 2023; Hoyer *et al.* 2017; Jordahl *et al.* 2020) and local parallel computing clusters were built with `dask` to increase computational efficiency (Rocklin 2015). Beta regression models were fitted using `brms` (Bürkner 2017), a package that interfaces with the Bayesian programming language `Stan` (Stan Development Team 2023), and analyzed in the `R` ver. 4.5 environment (R Core Team 2025). Models were run with weakly informative priors and 4 chains with 2000 iterations each. Model fits were visually evaluated by comparing observed values against posterior predictive draws. Convergence was assessed by ensuring Rhat <= 1.01 and bulk ESS > 400 (Vehtari *et al.* 2021). The packages `tidyverse` and `cowplot` were used to wrangle and visualize data (Wickham *et al.* 2019; Wilke 2019).

S-2: Results & Discussion

I. Overview

Between 2015 and 2024, 14.2% of fires (549 out of 4039 fires) in the emissions inventory relied on daily perimeters mapped by FEDS. Most emissions estimates that instead rely on CAL FIRE perimeters (due to the fire lasting only one day or not having sufficient VIIRS AFP for implementing FEDS) were from fires that were both short-lived and small (Fig. 1). According to alarm and containment dates in CAL FIRE records, 53% of fires using CAL FIRE perimeters burned for just one day and 95% lasted 14 days or less. In contrast, the 50th and 95th percentile of fire duration for FEDS fires was 29 and 134 days, respectively. The median fire size for those using the CAL FIRE dataset was 23.2 acres, compared to 2063 acres for fires mapped by FEDS. While most fires in this inventory were mapped using CAL FIRE perimeters, FEDS perimeters had the greatest impact on it, accounting for 94.3% of the acres burned, 95.8% of the fuel consumed, and 96.3% of the $PM_{2.5}$ emissions. As a result, CARB's emissions inventory has shifted dramatically, with the bulk of estimates now resolved at the daily scale, capturing emissions with unprecedented detail.

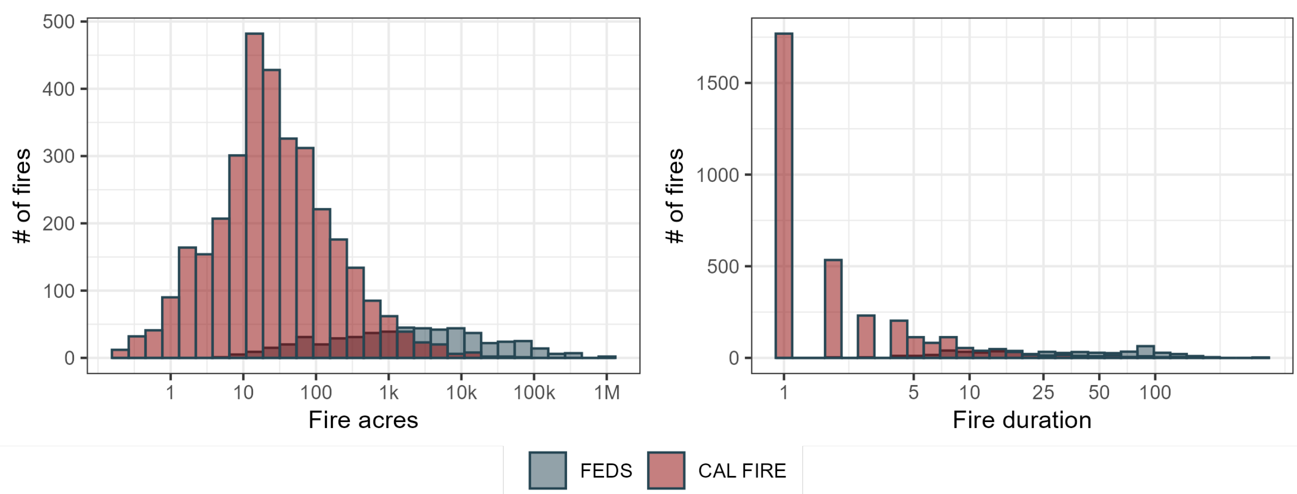

Figure 1. Fire size and duration for incidents mapped using CAL FIRE and FEDS perimeters (2015–2024).

II. Performance of FEDS Perimeters

A. Absolute differences with CAL FIRE perimeters

The accuracy of all FEDS perimeters (n = 549) was assessed by comparing the final perimeters to CAL FIRE perimeters. In general, there was strong agreement between FEDS and CAL FIRE perimeter size (R^2 = 0.93, slope = 1.12, Fig. 2). FEDS tended to overestimate the size of fires under 1,000 acres, with accuracy improving as fire size increased. This pattern likely reflects the 375-meter spatial resolution of VIIRS, which introduces a minimum level of coarseness that disproportionally enlarges small fires more than big fires. For larger fires, constraining VIIRS pixels to CAL FIRE polygons can have the opposite effect, sometimes biasing FEDS toward underestimating perimeter size and leading to non-gaussian residuals. The spatial alignment between FEDS and CAL FIRE perimeters was generally good (Fig. 3), with a median F1 score of 0.77 (10th–90th percentile: 0.42–0.92) and a median IoU of 0.63 (0.26–0.85). To illustrate how IoU values translate into visual overlap, see Fig. S1. User's accuracy had a median of 0.74 (0.33–0.91), while producer's accuracy was higher at 0.97 (0.58–1.00), indicating that the model effectively captured observed burn area but also generally produced false positives. Given that the modifications to FEDS involved constraining VIIRS pixels to CAL FIRE perimeters, it is unsurprising that FEDS aligned well with CAL FIRE perimeters.

To understand the factors influencing IoU, a series of beta regression models were fitted that included different combinations of predictors relating to fire size, duration, and vegetation composition. Leave-one-out cross-validation indicated that several models including fire size and vegetation composition had equivalent predictive performance (ΔELPD within the standard error). The selected model included fire size and proportion of forest and woodland vegetation as covariates, capturing the key predictors while remaining simple and interpretable. Replacing fire size with fire duration substantially worsened predictive performance (ΔELPD = -166.2, SEΔ = 62.9), and modeling the precision parameter of the beta distribution as a function of covariates offered no improvement. The mean of the beta distribution was positively associated with log-transformed fire area (median = 1.52, 5^{th}–95^{th} credible interval = 1.40–1.65) and forest and woodland composition (median = 0.53, 5^{th}–95^{th} credible interval = 0.35–0.70). These results suggest that FEDS performs better for larger fires and, to a lesser extent, for those dominated by forest and woodland vegetation (Fig. 4). This means that FEDS is most accurate where it matters: the highest emitting fires tend to be large and occur in forests and woodlands where fuel loading is greatest.

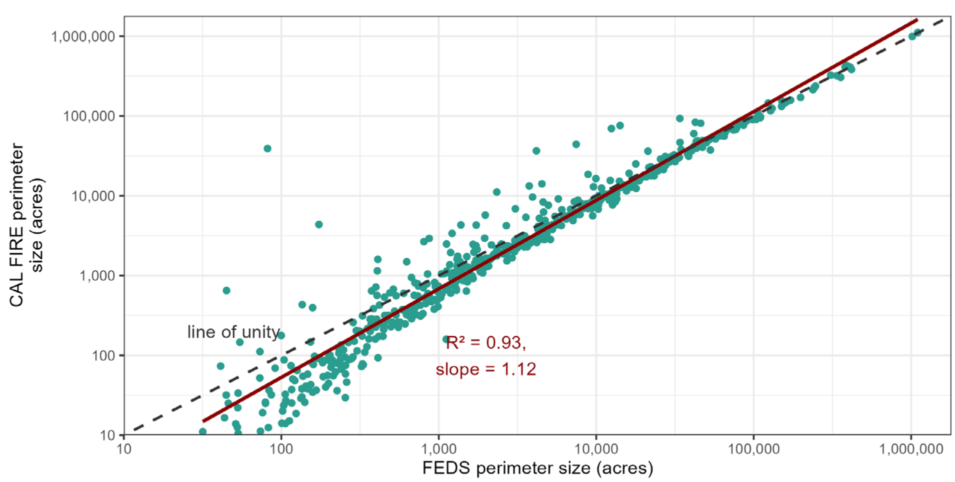

Figure 2. Comparison of final fire sizes from FEDS versus CAL FIRE perimeters (n = 549). The regressed line (red) is overlaid on top of the line of unity (black dashed).

For 32 fires, daily perimeters were compared with those mapped by aerial IR (Table S1). Since aerial IR data is not available for every wildfire, nor is it organized in a consistent format, the sample size was more limited than the comparison with CAL FIRE perimeters. Additionally, fires that had IR data tended to be larger and occurred in forest- and woodland-dominated ecosystems, biasing FEDS perimeters towards greater spatial agreement with ground-truthed perimeters. With that said, results similarly show good F1 scores, IoU, user's accuracy, and producer's accuracy, with values increasing to high levels (e.g. >0.75 IoU) for fires persisting over 5–10 days (Fig. S2).

B. Relative differences with aerial infrared perimeters

Thus far, absolute differences in perimeter sizes have been evaluated, but since all FEDS-derived values of burned area, emissions, and consumption are proportionally scaled to match those from CAL FIRE perimeters (eq. 4-5), arguably, relative cumulative growth rates provide a more meaningful metric for assessing performance. Relative cumulative growth rates of FEDS perimeters were compared to those from aerial IR data, the NEI, and an estimate based on fractional daily counts of VIIRS AFP (Fig. 5). The results show that FEDS perimeters closely aligned with aerial IR data, with an average RMSE of 0.04 (SD = 0.03). This was significantly better than both the VIIRS-based estimate (log-Δ = 0.55, $p = 0.038$) and the NEI (log-Δ = 1.00, $p < 0.001$) (Fig. S2). The VIIRS-based estimate also aligned well with aerial IR data, though slightly less so than FEDS (RMSE mean = 0.07, SD = 0.04). The NEI aligned the least well with aerial IR data (RMSE mean = 0.12, SD = 0.09). However, the difference between the VIIRS-based estimate and the NEI was only marginally statistically significant (log-Δ = 0.45, $p = 0.10$).

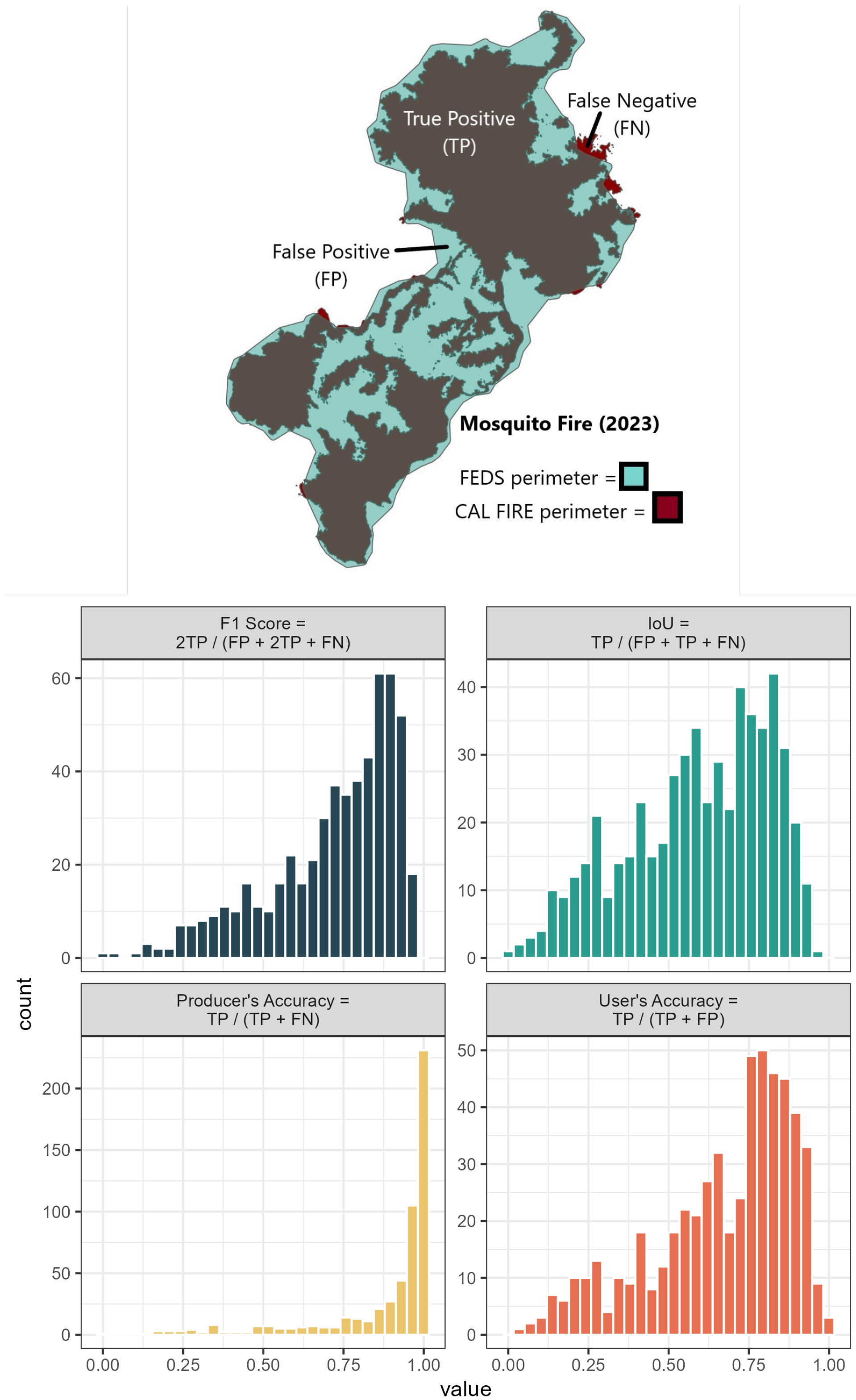

Figure 3. Distribution of spatial accuracy metrics (F1 score, IoU, user's accuracy, and producer's accuracy) for FEDS perimeters compared to CAL FIRE perimeters. Top image illustrates how true positives, false positives, and false negatives were defined based on spatial overlap of FEDS and CAL FIRE perimeters.

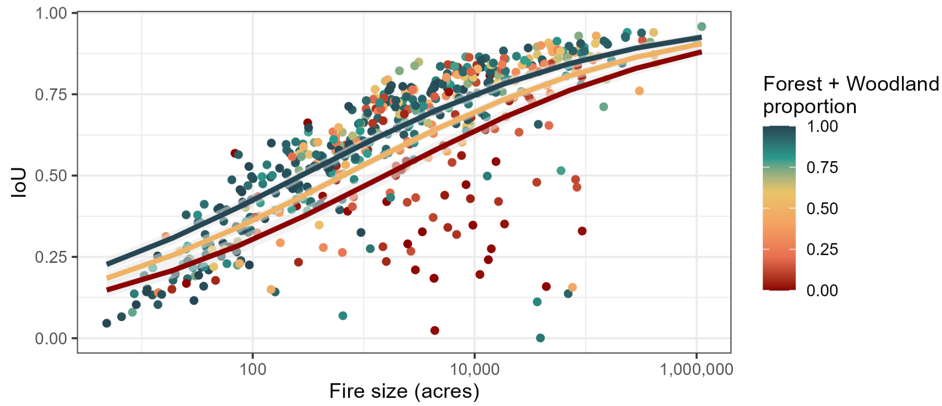

Figure 4. Intersection over Union (IoU) predicted by a combination of fire size and forest and woodland composition using a beta regression. Lines represent the mean model for fires with the 10th (red), 50th (yellow), and 90th (blue) percentile of forest and woodland proportion. Grey shaded region around the lines denotes the posterior's 90th credible interval.

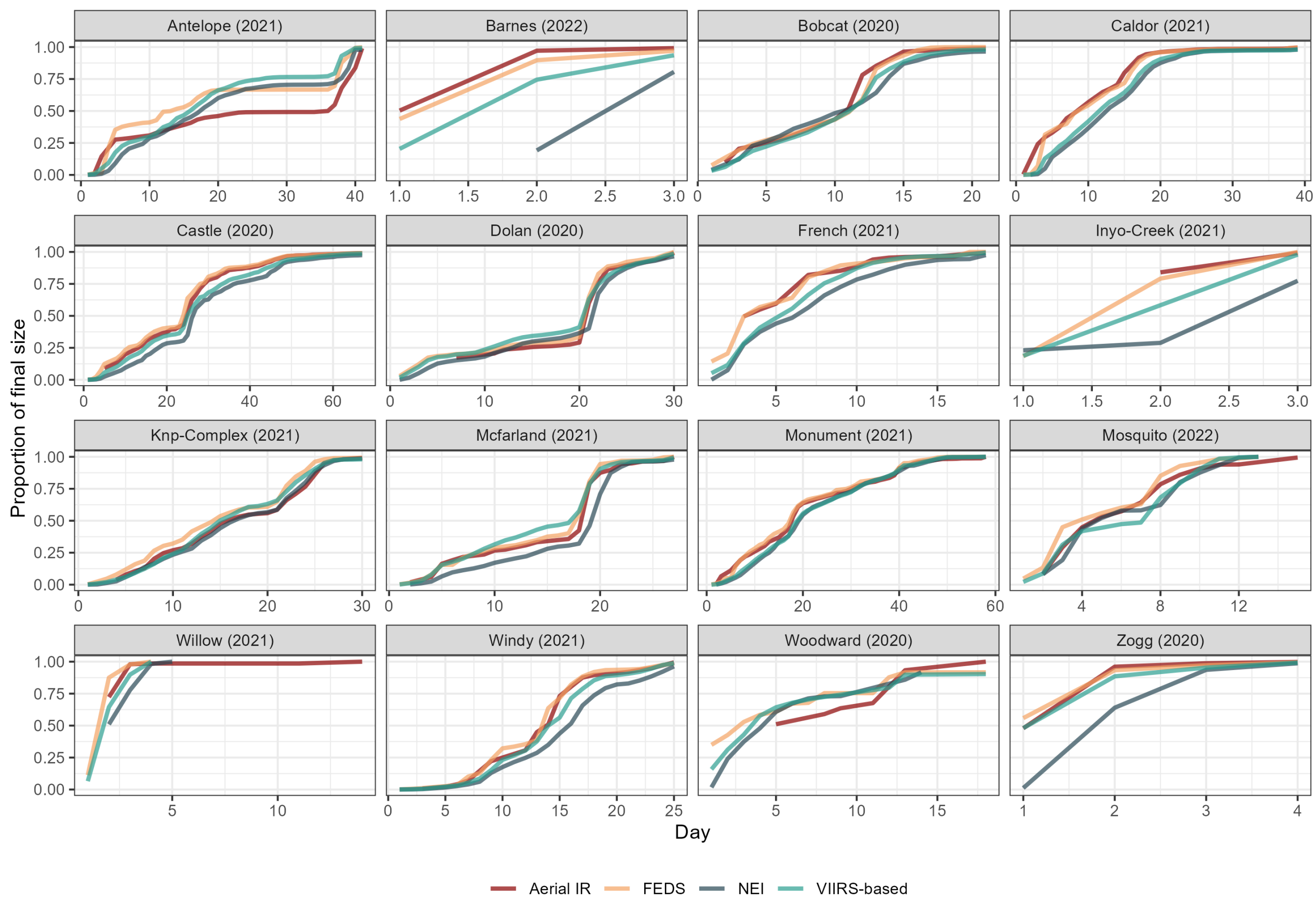

Figure 5. Cumulative relative fire growth for 16 randomly selected fires, comparing FEDS perimeters (yellow) to aerial IR data (red), VIIRS AFP-based estimates (teal), and the NEI (blue).

These findings indicate that FEDS reliably captures relative fire growth over time. The NEI shows the largest deviations from aerial data, which is understandable given that its inventory spans all 50 states. Emissions allocated based on fractional VIIRS AFP—which CARB used to support a recent State Implementation Plan report (San Joaquin Valley Air Pollution Control District 2024)—provide a reasonable approximation of fire size when perimeter-based data are unavailable. However, because this approach does not align fuelbed and fuel moisture data in space and time, the resulting emissions estimates carry additional uncertainty compared with FEDS.

III. Emissions comparison

Aggregated daily emissions of $PM_{2.5}$ calculated from FEDS perimeters (n = 183) closely matched the total bulk emissions calculated from the corresponding CAL FIRE perimeters (R^2 = 0.999, slope = 0.98). Summing the daily FEDS-based estimates yields total emissions that are consistent with CAL FIRE-based calculations, suggesting that the updated inventory—incorporating daily fire perimeters—is well-calibrated and aligned with the methodology used in previous CARB inventories.

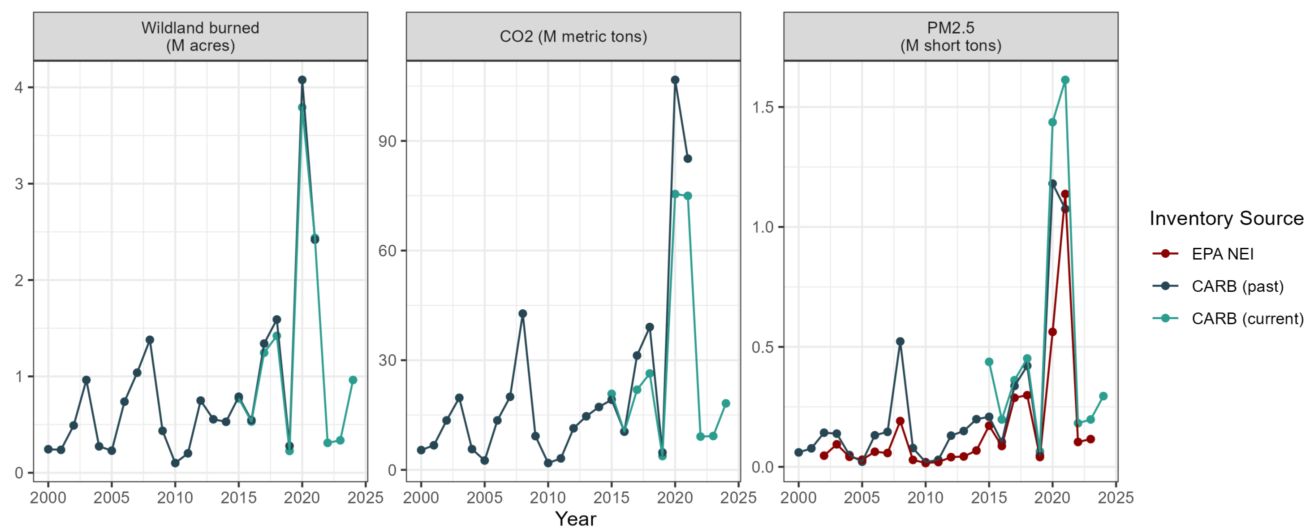

Figure 6. Comparison of wildfire emissions estimates across CARB's past and current inventories and the US EPA NEI. Panels show annual totals for wildland acres burned, CO_2, and $PM_{2.5}$ emissions.

Comparisons of wildfire emissions inventories reveal both congruencies and divergences (Fig. 6). Overall, past and current CARB inventories report similar wildland acres burned, though slight year-to-year deviations exist. These differences primarily stem from the Fuel Characteristic Classification System (FCCS) fuelbed sources used in each inventory (see Fig. S4 for additional inference). The past CARB inventory relied on FCCS fuelbeds produced by a contractor, who interpolated in-between years using multinomial models to address the fact that LANDFIRE (*www.landfire.gov/data*) releases FCCS vintages in non-consecutive years (University of California, Berkeley 2019). In contrast, the current inventory uses FCCS fuelbeds directly from LANDFIRE to align with the broader scientific community. When one

FCCS source assigns a cell as agricultural or developed land, while the other assigns it as naturally vegetated, the total acres of burned wildland will differ. These differences in fuelbed sources explain much of the variation observed between the past and current CARB inventories.

CO_2 emissions from the past CARB inventory are consistently higher than those from the current inventory (Fig. 6). Like the wildland acres burned, this variation is driven primarily by the change in FCCS fuelbed source. When EFs are held constant, LANDFIRE FCCS produces lower CO_2 estimates than the contractor-derived FCCS used previously (Fig. S4). Expanded EFs adopted in the current inventory have only a minor effect on CO_2 (e.g. expanded EFs for dominant western forest ecosystems produce 0.90x flaming and 1.13x smoldering compared to default EFs; Table S1). Thus, the decrease in CO_2 relative to the past CARB inventory reflects changes in fuelbed inputs.

$PM_{2.5}$ emissions in the current CARB inventory are generally higher than the past CARB inventory (Fig. 6), reflecting the combined effects of switching to LANDFIRE FCCS fuelbeds and adopting expanded EFs (Fig. S4, Table S1). Unlike CO_2, $PM_{2.5}$ is strongly affected by the EF choice: for western forests—the dominant land type in California wildfires—expanded EFs increase flaming emissions by 8.9x and smoldering by 1.5x, leading to systematically higher statewide totals. A notable observation is the increase in $PM_{2.5}$ from 2020 to 2021, despite 2020 burning ~50% more acres. This counterintuitive result likely reflects two factors: first, LANDFIRE recorded about 125k more acres of forested land burned in 2021, and forests carry higher fuel loads and thus produce more particulate emissions than shrublands or grasslands. Second, the inventories draw on different LANDFIRE FCCS vintages across those years—2020 uses LF2016 while 2021 uses LF2020—introducing a step change in the fuelbed data that likely amplifies the discontinuity between years.

When compared to the EPA's NEI, CARB inventories—both past and current—show substantial divergence, which stems from methodological differences. The NEI is based on another model that estimates emissions, Consume (Ottmar *et al.* 1993), rather than FOFEM, and Consume has been shown to generally estimate less fuel consumption and emissions than FOFEM (Kennedy *et al.* 2020). Additionally, the NEI uses EFs from Smoke Emissions Reference Application (Prichard *et al.* 2020) and Urbanski (2014), which align closely with CARB's EFs but only for 2021-2023; for earlier years, their methodology differs substantially. Thus, the discrepancies between CARB and NEI are not surprising and are consistent with the long-standing differences observed between the NEI and the past CARB inventory.

S-3: Supplementary Figures and Tables

Figure S1. Visual examples of spatial overlap between FEDS (multicolored) and CAL FIRE (red) perimeters for fires exhibiting a range of Intersection over Union (IoU) values. The color ramp in the FED perimeters corresponds to duration of fire. Fire names concatenate the year, fire name, and incident number from the CAL FIRE perimeter dataset.

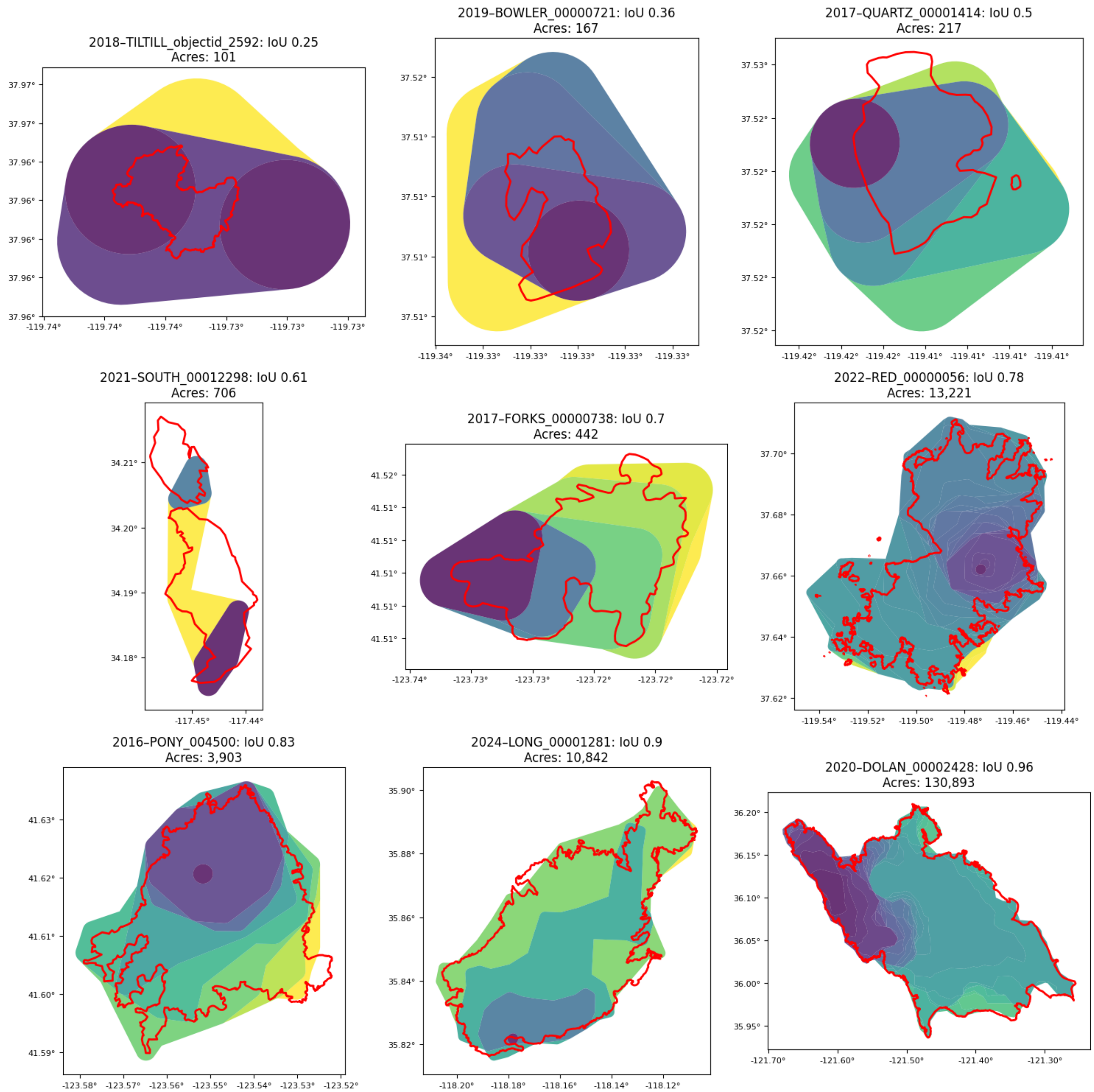

Figure S2. Spatial agreement between FEDS and aerial IR perimeters for 32 fires (2020–2023), shown by days since FEDS' first detection. Lines represent the evolution of the spatial metric for a given fire. Point ranges show the mean value of each spatial metric within 5-day bins, with vertical bars indicating the 10th and 90th percentiles.

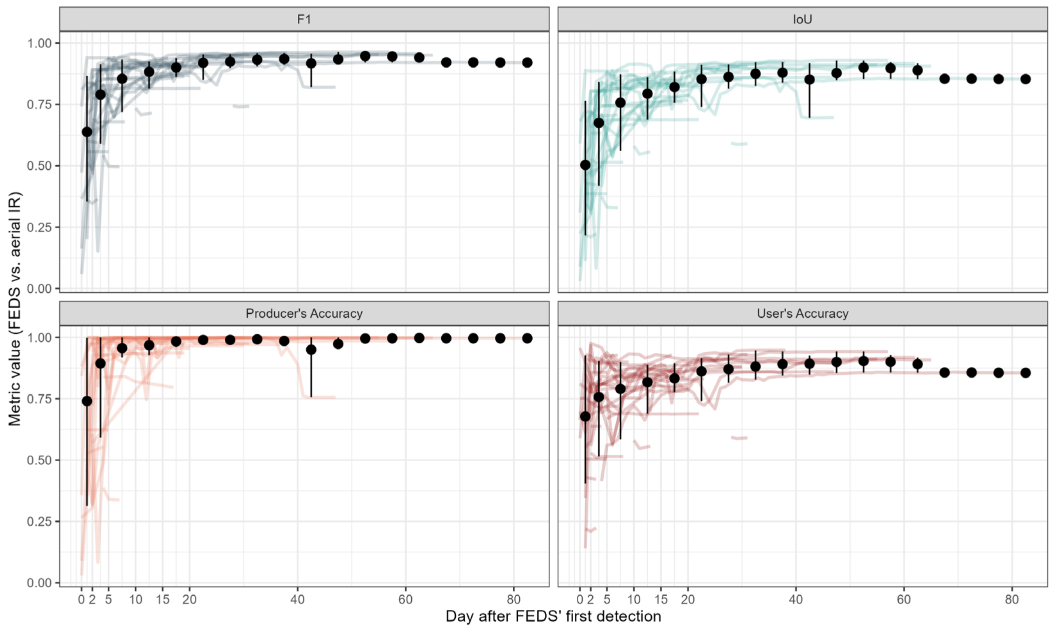

Figure S3. Log-RMSE of cumulative relative fire growth compared to aerial IR data for FEDS, VIIRS-based estimates, and the NEI. FEDS showed significantly lower RMSE than both alternatives (letters denote statistically significant groupings; $p < 0.05$).

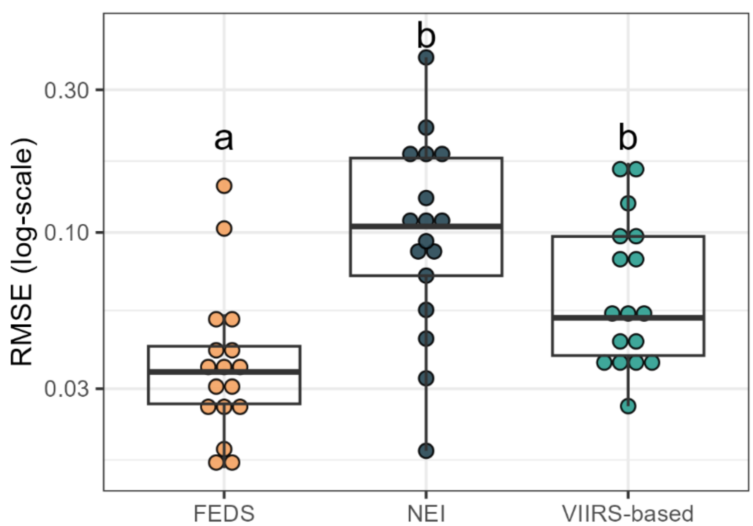

Figure S4. The past CARB inventory (blue) was compared to multiple inventory versions generated using the current CARB pipeline (hereafter "CARB Current [FCCS source, EF option]"). The past CARB inventory used FCCS fuelbeds from a contractor and the default EFs in FOFEM. When compared to CARB Current (FCCS contract, default EFs; yellow), statewide estimates aligned most closely. By contrast, CARB Current (LANDFIRE FCCS, default EFs; orange) produced fewer burned acres and lower CO_2 and $PM_{2.5}$ emissions across most years. These sequential comparisons indicate that, with emission factors held constant, the primary driver of change is the FCCS source. The final version of the CARB inventory (teal) incorporates LANDFIRE FCCS and expanded EFs. Relative to CARB Current (LANDFIRE FCCS, default EFs), there were substantial increases in $PM_{2.5}$ estimates—reflecting higher expanded EFs, especially for dominant western forests—while CO_2 shows only minor changes (see Table S1). Relative to the past CARB inventory, the current version therefore reflects both a shift in fuelbed source and the adoption of expanded EFs, yielding lower CO_2 but higher, vegetation-specific $PM_{2.5}$ estimates.

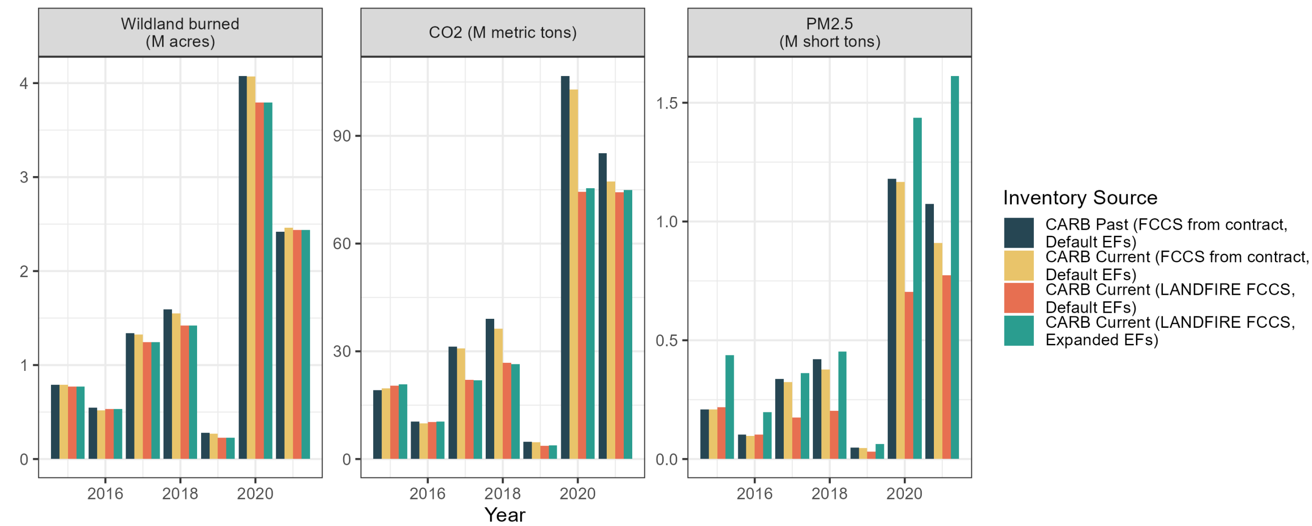

Table S1. Default emission factors reproduced from FOFEM (Lutes 2020) and ratios of expanded to default EFs for western forest wildfires. Default emission factors are derived from earlier research and are the same regardless of vegetation type (Finney 2001; Hardy *et al.* 1996; Ward *et al.* 1993). The ratios of expanded EFs to default EFs for western forest wildfires are presented for both flaming and smoldering phases. For example, $PM_{2.5}$ emissions in western forests are expected to increase by 8.91x in the flaming phase and 1.51x in the smoldering phase compared to default values. Because California fires burn through multiple vegetation types, these ratios do not represent the expected statewide change when using expanded EFs instead of default EFs, and the actual ratios will vary by pollutant and vegetation type.

Phase	**CO_2 g/kg**	**CO g/kg**	**CH_4 g/kg**	**NO_x g/kg**	**SO_2 g/kg**	**$PM_{2.5}$ g/kg**	**PM_{10} g/kg**
Flaming	1778.01	6.520	0.796	3.2	1.0	2.604	3.073
Smoldering	1228.11	301.72	13.756	0	1.0	22.644	26.720
Ratio $F_{expanded}$:$F_{default}$	0.900	20.7	9.20	0.625	1.06	8.91	8.92
Ratio $S_{expanded}$:$S_{default}$	1.13	0.806	0.796	Inf	0.880	1.51	1.51

Table S2. Summary of selected wildfires used to evaluate FEDS perimeters against perimeters estimated from aerial IR. Incident Number corresponds to the column name "INC_NUM" in the CAL FIRE perimeter dataset. Start and end dates are determined based on detected fire activity from VIIRS AFP and aerial IR. Acres and proportion of forest and woodland vegetation type are calculated from the CAL FIRE final perimeters.

Year	Fire Name	Incident Number	Start Date	End Date	Acres	Proportion Forest & Woodland
2020	Blue Ridge	20121612	10/26/2020	10/30/2020	13,699	0.01
2020	Bobcat	00003687	9/6/2020	10/6/2020	116,150	0.28
2020	Castle	00002541	8/20/2020	11/9/2020	171,009	0.84
2020	Creek	00001391	9/4/2020	12/10/2020	382,836	0.73
2020	Dolan	00002428	8/18/2020	10/1/2020	124,506	0.46
2020	Hennesey	00013337	8/17/2020	9/5/2020	305,121	0.42
2020	North Complex	00001308	8/17/2020	11/4/2020	318,938	0.93
2020	Point	00032344	10/26/2020	10/28/2020	93	1.00
2020	River	00004024	8/16/2020	8/30/2020	50,200	0.43
2020	Sheep	00001299	8/17/2020	9/5/2020	29,507	0.81
2020	Stump	00004290	8/1/2020	8/4/2020	325	0.97
2020	Woodward	00012009	8/18/2020	10/17/2020	4,899	0.91
2020	Zogg	00009978	9/27/2020	10/7/2020	56,272	0.29
2021	Antelope	00006454	8/1/2021	10/17/2021	145,419	0.76
2021	Caldor	00024030	8/14/2021	10/15/2021	229,038	0.92
2021	French	00002796	8/18/2021	9/10/2021	28,087	0.80
2021	Inyo Creek	00001299	6/20/2021	6/27/2021	601	0.32
2021	KNP Complex	00000122	9/10/2021	12/7/2021	91,473	0.86
2021	McFarland	00001175	7/29/2021	10/4/2021	122,308	0.59
2021	Monument	00001187	7/30/2021	10/11/2021	227,294	0.91
2021	Willow	00001493	6/17/2021	7/3/2021	2,877	0.72
2021	Windy	00003058	9/9/2021	10/29/2021	97,661	0.92
2022	Barnes	00000896	9/7/2022	9/14/2022	5,832	0.78
2022	McKinney	00006177	7/29/2022	8/26/2022	60,026	0.79
2022	Mosquito	00001371	9/6/2022	11/4/2022	76,706	0.94

Year	Fire Name	Incident Number	Start Date	End Date	Acres	Proportion Forest & Woodland
2022	Radford	00012958	9/5/2022	9/26/2022	1,080	0.80
2022	Rodgers	00000058	8/11/2022	10/17/2022	2,841	0.84
2022	Sheep	00001704	6/11/2022	6/15/2022	865	0.32
2022	Washburn	00000038	7/7/2022	9/15/2022	4,884	0.98
2023	Deep	00000973	8/15/2023	9/20/2023	4,206	0.97
2023	Pika	00000050	7/6/2023	8/7/2023	840	0.94
2023	York	00010701	7/28/2023	8/4/2023	93,077	0.01

S-4: References

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