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RESEARCH LETTER

Comparing ground-based lightning detection networks near wildfire points-of-origin

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Abstract

Lightning detection and attribution to wildfire ignitions is a critical component of fire management worldwide to both reduce hazards of wildfire to values-at-risk and to enhance the potential for wildland fire to provide resource benefits in fire-adapted ecosystems. We compared two operational ground-based lightning detection networks used by fire managers to identify cloud-to-ground strokes within operationally-relevant distances (1.6 km) of the origins of 4408 western United States lightning-ignited wildfires spanning May–September 2020. Applying two sets of constraints–varying holdover time and applying a quality control measure–we found strokes were co-detected near 55–65% of fires, increasing to 65–79% for detection by at least one network, with neither network detecting lightning near 1024–1666 fires. Because each network detected strokes near 136–376 unique fires, the use of both networks is suggested to increase the probability of identifying potential fire starts. Given the number of fires with network-unique detections and no detections by either network, improvements in lightning detection networks are recommended given increasing fire hazard.

Keywords Lightning · Lightning detection · Observational network · Western United States · Wildfire

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1 Introduction

In fire-prone environments, lightning detection informs wildfire managers about the potential for ignitions (Schultz et al. 2019). Lightning-ignited wildfires are an important component of the natural fire cycle in the western United States (wUS) and worldwide (Moris et al. 2023). In the wUS, lightning-ignited wildfires are associated with approximately 69% of burned area (Abatzoglou et al. 2016). However, increased fuel loading following over a century of fire suppression and fire exclusion combined with expansion of the wildland-urban interface has compounded the hazard lightning-ignited wildfires pose to life, property, and ecosystems (Keeley and Syphard 2021). Therefore, rapid identification and effective management of lightning-ignited wildfires is paramount to balance the resource benefits provided by wildland fire with its hazards (Pietruszka et al. 2023).

This work is motivated by the contribution of lightning ignitions to the active 2020 fire season in the wUS (Rudlosky et al. 2020). Lightning is common during the warm season in the eastern portion of the wUS (Fig. 1a), with the majority of lightning-ignited fires occurring between June-August when 100–1000 h fuel moistures reach their climatological minima (Abatzoglou et al. 2016) and temperatures, relative humidities, and solar radiation favor higher probabilities of ignition. The 2020 warm season brought anomalously more lightning to the wUS, with the World Wide Lightning Location Network (WWLLN; Kaplan and Lau (2021)) indicating more lightning activity than 2011–2021 means in the far western and northwestern United States but less lightning than average in the southern, central, and eastern portions of the wUS (Fig. 1b). Anomalous positive lightning detections in California were associated with poleward transport of remnant moisture from a decaying tropical storm interacting with a favorable environment for elevated convection and dry thunderstorms whereas less lightning activity than normal during 2020 in Arizona, New Mexico, Colorado, and Utah was associated with a weak North American Monsoon (Nauslar et al. 2019).

A confluence of factors in 2020 led to more widespread fire activity than normal, especially in California (Keeley and Syphard 2021) and the Pacific Northwest (Higuera and Abatzoglou 2021), culminating in numerous negative economic and health impacts (D'Evelyn et al. 2022). The factors included ignitions from dry lightning outbreaks (Nauslar and Hatchett 2019; Rudlosky et al. 2020), limited suppression resource availability (Belval et al. 2022) and highly receptive and overstocked fuel beds capable of producing extreme fire behavior once ignited as drought conditions worsened from May (Fig. 1c) through August (Fig. 1d) and into September (Fig. 1e), with a September downslope offshore wind event driving rapid spread and extreme fire behavior (Abatzoglou et al. 2021; Higuera and Abatzoglou 2021).

Given the active 2020 wildfire season and concerns for an increasing potential for similar fire seasons as fuels continue to accumulate amidst a drying climate, the 2020 wildfire season serves as a useful case study to compare two operational lightning detection networks. Here, we assess their ability to detect lightning at spatial and temporal scales relevant to fire management.

2 Data

2.1 Wildland fire occurrences

Wildland fires during May-September 2020 were identified using the United States Forest Service's Fire Occurrence Database (FOD; (Short 2022)). The FOD only

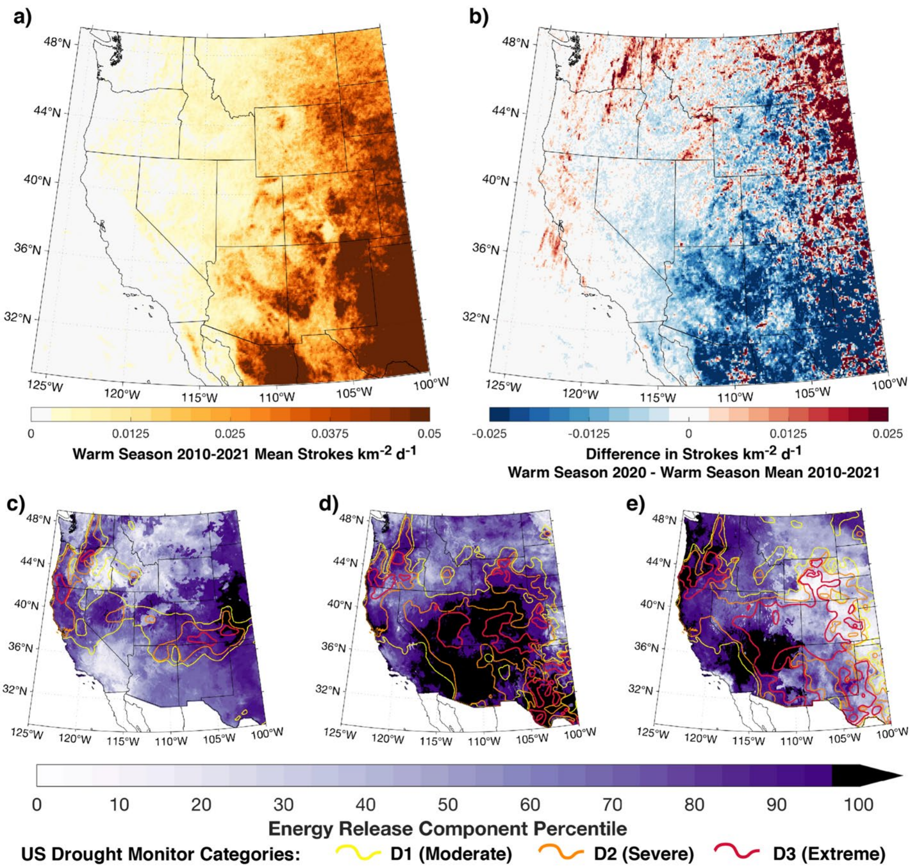

Fig. 1 **a** Climatological mean warm season (1 May–30 September) cloud-to-ground lightning strokes (*strokes* km^{-2} day^{-1}) spanning 2010–2020 for the western United States using 0.125° horizontal resolution monthly World Wide Lightning Location Network (WWLLN) data (Kaplan and Lau 2021). **b** WWLLN stroke differences (*strokes* km^{-2} day^{-1}) between the 2010–2020 mean and the 2020 warm season for the western U.S. **c** Gridded energy release component percentiles from the 4 km horizontal resolution gridMET product (Abatzoglou 2013) for 1 May 2020. Percentiles were calculated between 1979–2022. Higher percentiles indicate greater potential energy released per unit area of the flaming front of a head fire for the date calculated. Contour lines show United States Drought Monitor (https://droughtmonitor.unl.edu/) categories as of 5 May 2020 (yellow indicates moderate drought (D1), orange indicates severe drought (D2), and red indicates extreme drought (D3)). **d** As in **c** but for 15 August 2020. **e** As in **c** but for 9 September 2020

includes fires with ignition origins known to the nearest point on the Public Land Survey System grid (1.6 km horizontal resolution) and spans 1992–2020. We extracted all fires between 1 May and 30 September 2020 ($n = 4,408$) with a natural (i.e., lightning) ignition determination for the conterminous western United States (west of 100°W longitude).

2.2 Lightning detection networks

Ground-based networks have been employed since the 1950s to detect lightning (Bouchard et al. 2023). The National Lightning Detection Network™ (hereafter NLDN), operated by Vaisala, Inc. (Orville 2008) and the Earth Networks Total Lightning Network® (hereafter ENTLN), operated by Earth Networks, Incorporated (Liu and Heckman 2011) are two major ground-based systems used in North America. Bitzer and Burchfield (2016) used a Bayesian approach to compare ground-based lightning detection networks globally between November 2014 and October 2015, finding that a combined Vaisala network composed of NLDN and the Global Lightning Detection 360 (Said et al. 2013) network detected 59.8% of discharges and ENTLN detected 56.8%.

The performance of lightning detection networks are continuously reviewed as the networks are upgraded with improved sensor technology and/or central processing algorithms (Vagasky et al. 2024). Zhu et al. (2016) reported NLDN CG stroke detection efficiencies of 92% (improving to 97% following network upgrades in 2021; Murphy et al. 2021). An assessment of lightning strikes to towers in the contiguous United States indicated a median NLDN CG location accuracy of 84 m (Zhu et al. 2020). Additional summarized performance metrics for NLDN can be found in Vagasky et al. (2024). After the most recent sensor and algorithm upgrades to the ENTLN in 2021, Zhu et al. (2022) performed an assessment in northern Florida. Zhu et al. (2022) found a detection accuracy of 92 m and detection efficiencies of 94% and 88% for natural and rocket-triggered lightning, respectively.

Point-based detections of CG lightning strokes from 1 May 2020–30 September 2020 for the wUS were acquired in native formats from ENTLN and NLDN. We used CG lightning strokes instead of lightning flashes because one lightning flash can be an aggregation of multiple strokes, and each stroke is a potential wildfire ignition source.

3 Methods

We performed two sets of comparisons between the two networks. Both comparisons utilized the same spatial proximity requirement—counting only CG lightning strokes within 1.6 km of the fire origin location—as this is the accuracy required for inclusion in the FOD dataset (Short 2022). Our first comparison—the less-strict approach—included a longer holdover period (14-days) to account for rare, but occasional, long-duration holdover fires and it included all CG lightning strokes (no quality control was applied). The second, more-strict approach, applied a simple quality-control filter to remove strokes between −10 kA and 10 kA because these weaker IC strokes can be mis-classified as CG lightning (Abatzoglou et al. 2016; Schultz et al. 2019). The more-strict approach reduced the holdover time to three days before the fire report date as the majority of lightning fires are observed within this period (Schultz et al. 2019; Moris et al. 2023), and this is a common period during which operational forecasters have access to lightning data. For both comparisons, we also counted CG lightning strokes in the day after the reported discovery date to account for potentially misreported dates (Schultz et al. 2019).

To compare the correlation of total counts of CG lightning detections between networks at the origin-scale, we calculated Spearman's rank correlation coefficient for all fires with at least one CG lightning detection from at least one network. To compare whether the detection results from the two networks were significantly different, we performed a non-parametric McNemar's test on the 2×2 contingency table created for both networks detecting lightning within the specified criteria (a), individual network detections (diagonals b and c), or both networks missing detections (d). The test statistic is reported as $\mathcal{X}^2 = \frac{(b-c)^2}{b+c}$, which has a chi-squared distribution with one-degree of freedom for $b + c > 25$. The test was performed on both sets of paired data resulting from the less- and more-strict approaches.

4 Results

For the less-strict detection criteria, no lightning was detected near 1024 fires and both networks detected lightning near 3228 fires (65% co-detection; Fig. 2a). In the more-strict detection criteria case, no lightning was detected near 1666 fires and lightning was co-detected near 2626 fires (55%; Fig. 2b). The less-strict criteria identified 323 fires that only the NLDN network detected lightning near (within 1.6 km). This criteria identified 229 fires that only the ENTLN detected lightning near (Fig. 2c). Including these network-unique fires increased the total detection in the less-strict case to 79% of reported fires. The more-strict criteria increased the NLDN-only detections to 376 fires and lowered the ENTLN-only detections to 136 fires (Fig. 2d). This more restrictive case lowered the total percentage of detections by any network to 65%. In both cases, McNemar's test indicated statistically significant differences between the two datasets, with $\mathcal{X}^2 = 16.07, p = 0.0000063$ for the less-strict case, increasing to $\mathcal{X}^2 = 112.5, p = 0$ for the more-strict case.

For both detection criteria, total strokes were positively correlated between ENTLN and NLDN (Spearman's $\rho = 0.828$ for the less-strict criteria and Spearman's $\rho = 0.809$ for the more-strict criteria, respectively; Fig. 2e, f). In the less-strict case, ENTLN tended to detect more strokes than NLDN as evidenced by the least-squares line being shallower than the one-to-one line, though this was not always the case.

To further contextualize season-aggregated results, we also show an example from the 14–20 August 2020 "Lightning Siege" (Fig. 3) that ignited fires throughout the wUS as drought conditions worsened and energy release components increased (Fig. 2c). At the wUS scale, quality-controlled CG lightning shows similar patterns in space and time between the two networks but with different counts (66,755 NLDN strokes versus 46,448 ENTLN strokes; Fig. 3a, b). Focusing on a region of northern California and western Nevada that experienced 105 fire starts during this period, the general correlation between network detections is evident (Fig. 3c). The percentage of fires with lightning detected nearby (star symbols; $n = 66$; 63%) and no lightning detected (square symbols; $n = 39$) is similar to our wUS-wide results (65%). While the Sheep and Loyalton Fires included lightning detections near fire origins, the North Complex did not have lightning detected within 1.6 km of its three ignition locations (Fig. 3c). Lightning was detected near 25 ignitions ultimately composing the August Complex but 11 ignition locations did not have detections nearby (Fig. 3c).

5 Discussion

To our knowledge, no direct comparisons of these two ground-based lightning products, NLDN and ENTLN, exist at spatial scales pertinent to wildfire origins, despite documented needs for such comparisons (Rudlosky et al. 2020). A challenge in evaluating the skill of lightning detection methods is that beyond intentional experiments, direct comparisons

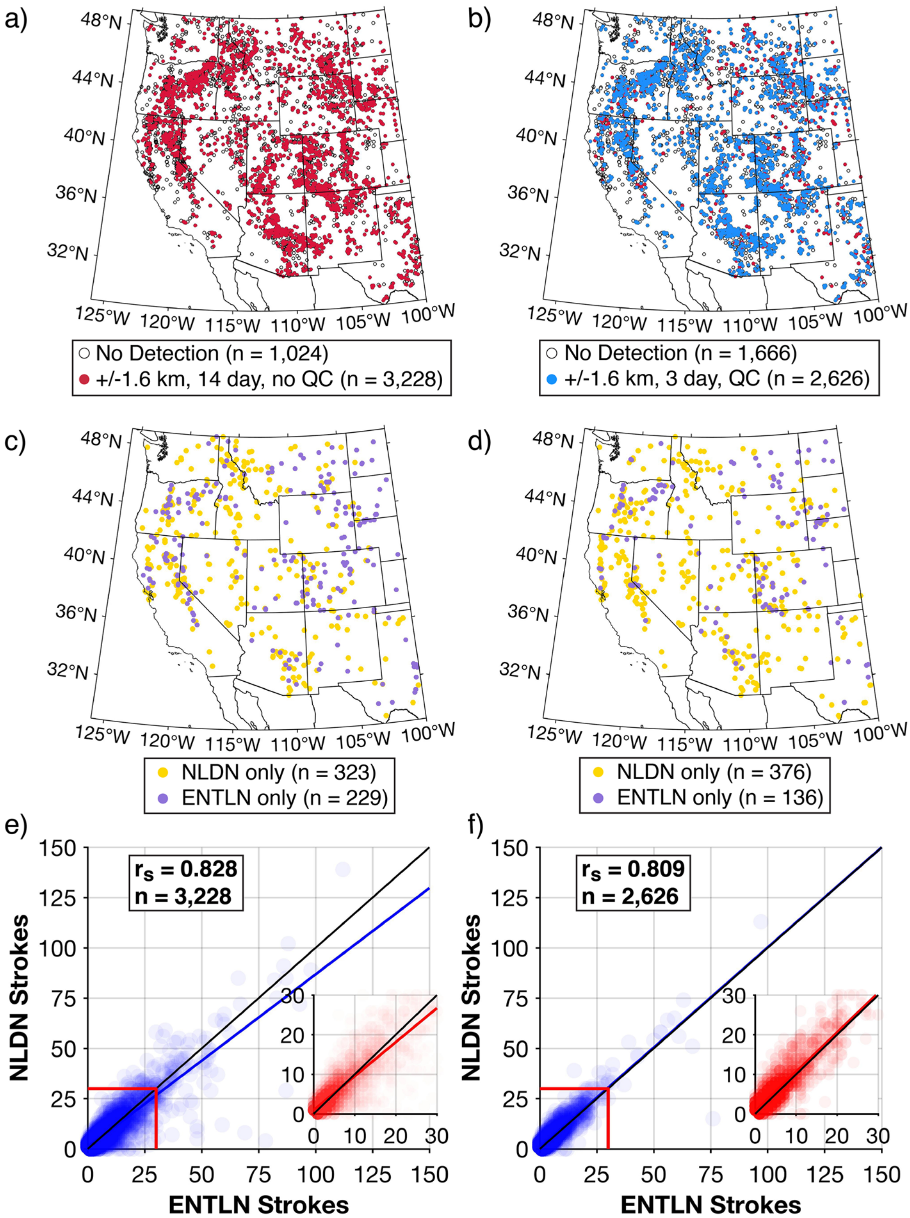

Fig. 2 **a** Open circles indicate fires that did not have lightning detected within the less-strict criteria (within 1.6 km, 14-day holdover, no quality control applied). Filled red circles indicate fires with lightning detected within the less-strict criteria. **b** As in **a** but using the more strict criteria (three-day holdover period and applying the quality control measure to remove strokes less than |10| kA) (filled blue circles). Red circles from **a** shown for comparison. **c** Gold (purple) circles show NLDN (ENTLN) detections only for the less-strict criteria. **d** As in **c** but for the more-strict criteria. **e** Scatterplot of ENTLN and NLDN strokes for fires with at least one detection from either network for the less-strict criteria. Black line is the one-to-one line while the blue line is the least-squares fit. The inset shows the zoomed region outlined in red. **f** As in **e** but for the more-strict criteria

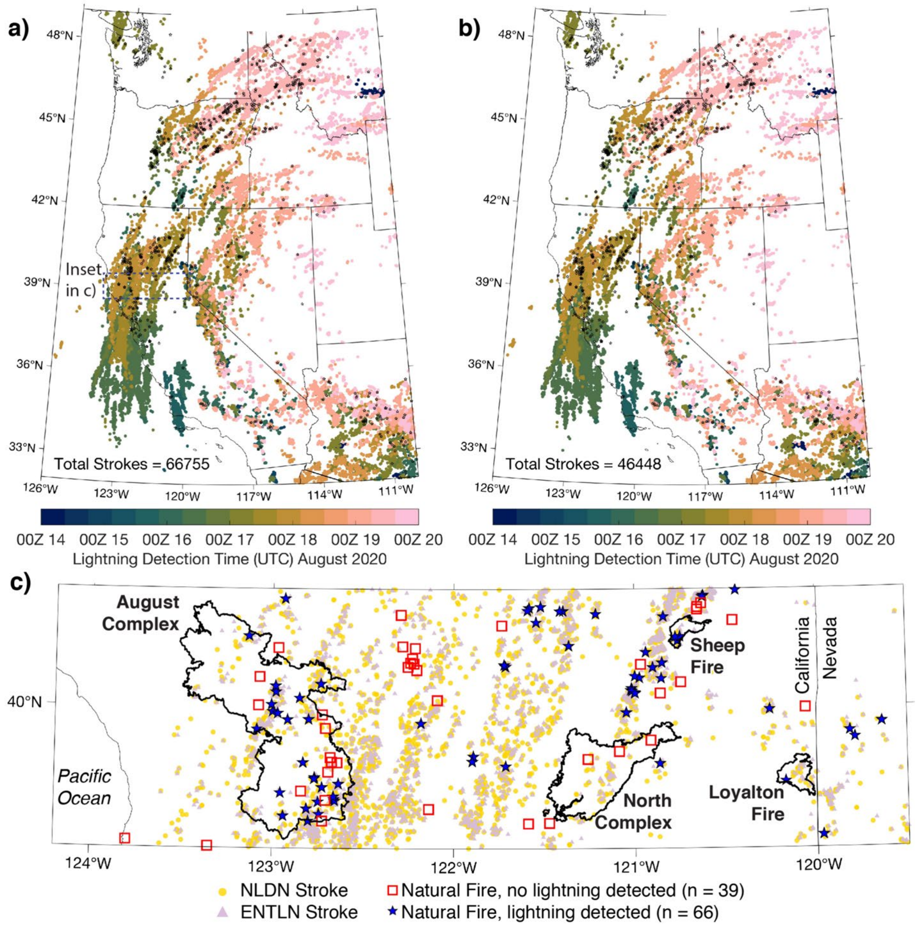

Fig. 3 **a** Quality-controlled cloud-to-ground (CG) lightning strokes between 14–20 August 2020 detected over the western United States by the National Lightning Detection Network (NLDN). **b** As in **a** but for the Earth Networks Total Lightning Network (ENTLN). Natural fires igniting during this period are shown as small black star symbols in **a** and **b**. **c** Zoom-in of the same period for northern California showing fire perimeters from the Monitoring Trends in Burn Severity dataset (https://burnseverity.cr.usgs.gov/viewer/?product=MTBS). Open red square symbols indicated fire ignitions with no CG lightning strokes detected within 1.6 km and filled blue star symbols show fires with CG lightning strokes detected nearby

are difficult due to imperfect knowledge of actual lightning (Virts and Koshak 2023). Our approach using high-accuracy lightning-ignited fire origins provides a first-order level of ground-truth for comparing networks.

Previous global-scale comparisons between ENTLN and NLDN showed comparable detection efficiencies (56.8% and 59.8%, respectively; Bitzer and Burchfield (2016)). Under the assumption of wildfire ignitions as a ground-truth, our conservative results are broadly consistent with Bitzer and Burchfield (2016) as we found co-detections in 55% of wildfire cases (65% with at least one detection) for the more-strict detection criteria. Although our detection criteria maintained a strict spatial constraint consistent with the FOD dataset requirement (within 1.6 km; Short (2022)), the more-strict approach with a shorter three-day holdover period and the application of a quality control step is consistent with previous work (Abatzoglou et al. 2016; Schultz et al. 2019). Relaxing these criteria improves overall detection efficiency and reduces the detection efficiency differences between the networks (lower values of McNemar's test statistic). That said, with over 85% of holdover fires occurring within three days (Moris et al. 2023), our less-strict criteria likely over-counts lightning detections. It is not operationally feasible to monitor all CG strokes for multiple weeks or to respond to each stroke location even if 100% detection were achieved. Nonetheless, advances in satellite-based fire detection methodologies from geostationary and polar-orbiting satellites as well as camera-based platforms will support longer-duration monitoring for potential holdovers to grow into larger fires should conditions become more conducive for fire spread (e.g., with the onset of downslope winds (Abatzoglou et al. 2021)).

Although we found the unique detections between both networks to be significantly different, for the purpose of fire management, ideally all lightning is detected. Because between 136 and 376 fires would not be quickly attributed to lightning if only one network was used, this implies the individual networks can augment one another if used together. This also highlights both networks stand to gain from continued investments to improve detection efficiency, as between 1024 and 1666 fires went un-detected by either network. Although investigating each individual CG stroke is likely infeasible, knowledge of singular CG strokes in receptive fuels with potential for rapid spread or in proximity to values-at-risk as well as clusters of CG strokes provides situational awareness for fire management and supports early warning (i.e., 'warn-on-detection') when combined with fire detection and monitoring (Lindley et al. 2019).

There are caveats associated with the 4408 wildfire ignitions examined. This is potentially a minimum estimate of lightning-caused fires given that not all fires in the FOD database have a determined cause. This number may also be an over-estimate as it is possible that cases are included where lightning was not the actual cause. Finally, a major limitation of this effort is the singular warm season studied, which demonstrated notable spatial anomalies in lightning activity (Fig. 1b). Future work should temporally extend this analysis.

6 Conclusion

A comparison of the capability of two ground-based lightning detection networks to detect cloud-to-ground lightning strokes within close proximity to known wildfire origins (within 1.6 km) was performed for the warm season of 2020 in the western United States. We found both networks reasonably successful in co-detecting lightning at the wildfire origin scale but also that each network augmented the other as many network-unique detections occurred. For operational purposes of lightning detection to support fire management, we conclude both networks should be utilized if possible. Given the frequencies of network-unique detections as well as fires attributed to (un-detected) lighting, we recommend continued investment in improving detection networks. Accurate and precise detections of lightning will be paramount to identify and manage wildland fire ignitions in an environment characterized by continued warming, drying, and fuel accumulation.

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Data availability Lightning stroke data is available upon reasonable request.

Code availability MATLAB code is available upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Informed consent All authors consent to the submission of this work for publication.

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