Tracking Wildfires With Weather Radars

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Abstract

There is a need for nowcasting tools to provide timely and accurate updates on the location and rate of spread (ROS) of large wildfires, especially those impacting communities in the wildland urban interface. In this study, we demonstrate how fixed-site weather radars can be used to fill this gap. Specifically, we develop and test a radar-based fire-perimeter tracking tool that leverages the tendency for local maxima in the radar reflectivity to be collocated with active fire perimeters. Reflectivity maxima are located using search radials from points inside a fire polygon, and perimeters are updated at intervals of ~10 min. The algorithm is tested using publicly available Next Generation Weather Radar radar data for two large and destructive wildfires, the Camp and Bear Fires, both occurring in northern California, USA. The radar-based fire perimeters are compared with available, albeit limited, satellite and airborne infrared observations, showing good agreement with conventional fire-tracking tools. The radar data also provide insights into fire ROS, revealing the importance of long-range spotting in generating ROS that exceeds conventional estimates. One limitation of this study is that high-resolution fire perimeter validation data are sparsely available, precluding detailed error quantification for the radar estimates drawn from samples spanning a range of environmental conditions and radar configurations. Nevertheless, the radar tracking approach provides the basis for improved situational awareness during high-impact fires.

Plain Language Summary

Weather radars effectively track the spread of high-impact wildfires in near-real time. Our method for radar-based fire tracking provides a new tool for fire and emergency management, helping to answer the questions “where is the fire now?” and “where will the fire be in the near future?”

1. Introduction

Our ability to warn for the impacts of large wildfires lags behind that of other weather-based disasters (Peace et al., 2020). Compare, for example, the accurate short-lead-time radar- and satellite-based warnings for severe thunderstorms (i.e., nowcasting) with the uncertainty surrounding the location and spread of wildfires. To be specific, no systematic mapping of wildfires meets nowcasting needs with most infrared (IR) fire observations suffering from either a lack of spatial (e.g., GOES16/17 data at 2 km pixels) or temporal resolution (e.g., IR flights once daily, polar orbiting satellites 4 times daily). This data gap was tragically underscored during California’s Camp Fire (Brewer & Clements, 2020; Mass & Ovens, 2021) wherein details of fire location and spread were largely unavailable to the public, confounding evacuation decisions with deadly consequences.

With this data gap in mind, the goal of this paper is to demonstrate the ability of fixed-location weather radars to track fire progression at high spatial and temporal resolution (e.g., hundreds of meters and tens of minutes). The motivation for this work is summarized in Figure 1, which shows fortuitously timed LANDSAT8 (hereafter L8) visible and IR satellite observations (Figure 1a) along with contemporaneous Next Generation Weather Radar (NEXRAD) radar reflectivity (Figure 1b) as the Camp Fire impacted Paradise, CA on 8 November 2018. This figure demonstrates the key attributes of the radar data that we will use to devise our radar-based perimeter tracking. Namely, local maxima in radar reflectivity closely correspond to active fire perimeters (e.g., McCarthy et al., 2019). Based on this inference, we develop an algorithm to track the fire’s progression using radar reflectivity and then test this algorithm against available IR observations of two high-impact wildfires, the Camp and Bear Fires.
2. Current Fire-Tracking Capabilities

Presently, satellite and airborne IR remote sensing provide the backbone for operational fire tracking by quantifying the fire perimeters, fire radiative power (FRP), fire-size, and fire temperature (Schroeder et al., 2014). These data are available from both polar orbiting and geostationary satellites. The polar orbiters (e.g., Moderate resolution Imaging Spectrometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS)) provide high spatial resolution fire detections (1 km for MODIS and 375 m for VIIRS), but only 4 times daily. These fire detections provide important snapshots of fire activity but are insufficient to track fire progression in real time. Filling this temporal data gap, the GOES-16 and -17 geostationary satellites provide greater time resolution (0.5–5 min), albeit at much lower spatial resolution (2 km resolution for the 3.9 μm band used in fire detection), which affect the sensitivity to sub-pixel fires (see details of GOES fire detection algorithms in Schmidt et al., 2013). These data can provide early alerts for new fire ignitions (Lindley et al., 2016), indicate pyrocumulonimbus (pyroCb) initiation (Peterson et al., 2015), and quantify changes in the fire intensity linked to the onset of extreme fire behavior (Lareau et al., 2018). However, they lack spatial resolution to provide sufficient details on fire perimeter locations for most nowcasting needs (e.g., answering when will the fire impact a given neighborhood). In contrast, some other satellite IR sensing provides very high resolution, for example, 30-m pixels with L8...
(Figure 1a), but have a very low return intervals (8 days), which is inadequate for tracking sub-daily fire changes. In addition to temporal and spatial limitations, errors in satellite-based fire detection and perimeter monitoring can result from parallax and “hot plume detections” due to superheated gases and embers lofted in plumes. Other sources of false detection or missed detections, including sun glint and pixel saturation, respectively, also exist (Schmidt et al., 2013).

In contrast to satellites, aircraft IR provides very high resolution (∼10 m) fire perimeters. In the United States, once daily nighttime fire perimeters are collected as part of the National IR Operations (NIROPS). While these data are crucial for operations and fire management, their once daily interval precludes their use nowcasting. Likewise, while autonomous aircraft provide promising new approaches for fire tracking (e.g., Ambrosia et al., 2011; Moran et al., 2019), they are only sporadically available and do not yet provide a viable nowcasting option.

Whereas IR sensors measure fire processes directly, weather radars quantify the temporal and spatial evolution of “pyrometeors” (i.e., ash and debris) lofted into the atmosphere by the fire and thus indirectly measure changes in the fire intensity and location. This capability relies on radar’s sensitivity to pyrometeors suspended in wildfire convective plumes such that the radar reflectivity, Doppler velocity, and dual polarization data quantify plume structure, air flow, and plume composition, respectively (McCarthy et al., 2019, 2020).

While radar scattering by pyrometeors remains a topic of ongoing research, in general, the larger the radar reflectivity, the larger the pyrometer size and/or number concentration (McCarthy et al., 2019). Accordingly, reflectivity data can quantify variations in fire and plume properties, including changes in plume behavior (Murdoch et al., 2019), volume (Duff et al., 2018; Price et al., 2018), and vertical extent (Fromm et al., 2006; Lareau et al., 2018). These data can also be linked to changes in underlying fire properties. Duff et al. (2018), for example, examined fire’s growth rate using changes in the volume of radar observed ash plumes in Australia. McCarthy et al. (2019) further demonstrated that horizontal radar scans can track changes in fire perimeters, which are apparent as local maxima in the radar reflectivity. Building on this insight, in this paper, we further demonstrate how radar reflectivity can be used to track fire progression.

### 3. Developing a Radar-Based Fire-Tracking Method

#### 3.1. Radar Data

Data from a NEXRAD radar at Beale Air Force Base, CA (KBBX), are used to quantify wildfire plume processes during the Camp and Bear fires (see fire dates and locations in Table 1 and Figure 2a). Metadata for KBBX are listed in Table 1 and the radar’s proximity to the Camp and Bear Fires is shown in Figure 2a. NEXRAD radars use a 10-cm wavelength that is sensitive to pyrometeors (McCarthy et al., 2019). Observations suggest that the radar reflectivity is largest immediately above the fire, where the ash and debris are most concentrated, whereas downstream reflectivity decays due to dilution by clear ambient air and the fallout of pyrometeors. As such, local maxima in radar reflectivity proximal to the fire provide an estimate for the fire’s location as shown in Figure 1.

Radar beam blockage by topography can impede observing fires in complex terrain. We estimate beam blockage using standard beam refraction and a high-resolution Digital Elevation Model (DEM) (Krajewski et al., 2006;
Figure 2. (a) Overview of KBBX radar site (red square), terrain (shaded), station location (yellow markers), and fire perimeters (red and magenta polygons) (b and c) The fraction of beam power and power loss (in db) for the 0.5 deg scan from KBBX (d and e) The fraction of beam power and power loss (in db) for the 1.5 deg scan from KBBX.
Kucera et al., 2004). To be specific, a 2D Gaussian distribution of beam illumination (Kucera et al., 2004) is used along with the 30-m spatial resolution topographic data set from Shuttle Radar Tomography Mission (STRM, Farr et al., 2007) to estimate the beam power lost along each radar radial. Maps of the beam blockage and power loss, in decibels, for the nominal 0.5° and 1.5° beam elevations are provided in Figure 2 along with the Bear and Camp fire perimeters and terrain data. These estimates show severe beam blockage (∼100% loss) over the fire areas for the 0.5° scan, which preclude the use of these data. In contrast, the 1.5° beam blockage over the Camp Fire is minimal. Over the Bear Fire, the beam blockage is 40%–60% with power loss of up to 10 dB. Despite this partial beam blockage, and as we show in data examples throughout, high radar reflectivity with structure clearly linked to the fire is resolved in this “ground skimming” scan. In other words, the remaining 50% of the beam is filled with high concentrations of pyrometeors linked closely to the surface combustion. As such, these 1.5° data are well suited for tracking the fire progression and serve as the basis for our tracking algorithm for both fires.

3.2. Radar Preprocessing

Radar data are acquired from the National Oceanographic and Atmospheric Administration (NOAA's) big-data project hosted on the Amazon cloud at https://registry.opendata.aws/noaa-nexrad/ (last accessed 1 November 2021). These data are then preprocessed for use in the fire perimeter tracking. The preprocessing helps establish robust features in the data and eliminate noise and spurious radar features. In the VCPs used in this study, the radar conducts two successive sweeps at each elevation angle, but with different pulse repetition frequencies (PRFs). The first “reflectivity” sweep uses a larger PRF, yielding a longer unambiguous range. The second sweep uses a smaller PRF, yielding a larger Nyquist velocity, but a shorter unambiguous range. This second sweep, while focused on velocity observations, also provides reflectivity data. These sweeps are typically ∼1 min apart in time. To best capture the structure of the fire in each volume scan, we take the maximum reflectivity at each range (r) and azimuth (θ) point between these two sweeps for the 1.5° beam:

\[ \text{dbZ}(r, \theta) = \max \left( \text{dbZ}_1(r, \theta), \text{dbZ}_2(r, \theta) \right) \]

This “maximum” approach is used to provide a richer characterization of the fire front within the interval covered by the two successive sweeps without running the algorithm separately for each time (i.e., one-minute updating is not needed). We note that using just the first “reflectivity” sweep ultimately provides sufficiently similar results that we do not further examine this sensitivity (not shown).

Next, we filter noise in the data using two steps. First, we use a binary image mask to remove small groupings of isolated pixels from the data set. Next, a 5 × 5 point median filter is applied to reduce noise in the remaining data, yielding a smoothed reflectivity data set \( \text{dbZ}_{sm} \) from which we track the fire perimeters.

3.3. Perimeter Tracking Algorithm

The fire-perimeter algorithm extracts the 2D \( \text{dbZ}_{sm} \) array for each time step and then locates local reflectivity maxima linked to the fire perimeter by searching radially outward from points selected within an ellipse approximating the fire's shape. The code for the algorithm is developed in MATLAB (MATLAB, 2018). A visual example of the algorithm's performance during the Camp Fire is provided in Figure 3, and conceptual steps of the algorithm are as follows:

**Step 1.** For the first time step, the user defines a starting polygon approximating the fire perimeter \((x_{perim}, y_{perim})\) using a point-and-click graphical user interface. This enables the user to leverage knowledge about the initial location of the fire.

**Step 2.** An ellipse is fit to the initial polygon (e.g., the blue oval in Figure 3). Ellipses are useful for approximating the general shape of a fire (Anderson, 1983), and in this case, are only used to compute the primary growth axis (i.e., the major axis) of the more complex fire polygon. The ellipse fitting uses a least squares criterion based on a conic ellipse and the input vertices of the fire polygon (Ohad, 2021). Because the ellipse's major axis can extend beyond the fire's perimeter, we subsequently trim the major axis to only include points within the actual fire polygon. For example, in Figure 3a, the major axis (blue line through the ellipse)
extends slightly beyond the edges of the fire perimeter (light gray line). Next, the center, one-quarter, and three-quarter points of the major axis are identified (purple squares along the blue line in Figure 3a). These three points are used for a radial search for fire perimeter points, described in the next step. Three points, rather than one, are used to better capture growth along any flank of the fire and to create a better sampling of the perimeter.

**Step 3.** From the three search points along the major axis, we search radially outward for local maxima in radar reflectivity. This is accomplished by generating search radial vectors using 0.5° azimuthal steps around a 360° arc and by interpolating the underlying radar data to the search vector (see, e.g., search radials drawn in Figure 3a). Each search vector extends from the search point within the polygon to a location 10 km beyond the edge of the previous fire perimeter. The 10-km cutoff is used as it falls at the upper end of long-range spotting reported for most, but not all, fires (e.g., Storey et al., 2020).

The interpolation is accomplished using a scattered interpolant (https://www.mathworks.com/help/matlab/ref/triscatteredinterp.html) generated from the 2D reflectivity array ($dbZ_{sm}$) along with the x and y coordinates of each data point. The interpolation is linear, uses Delaunay triangulation, and produces a surface ($V$)

$$V = F(x, y, dbZ_{sm})$$

which can be evaluated to yield the reflectivity value ($dbZ_{int}$) at the points along the search vector ($x_i$, $y_i$)

$$dbZ_{int} = V(x_i, y_i)$$

Examples of $dbZ_{int}$ along selected search radials are shown in Figures 3b–3d corresponding to the colored search radials in Figure 3a.

**Figure 3.** Example of the radar perimeter tracking algorithm for the Camp Fire at 1706 UTC on 8 November 2018. (a) Radar reflectivity (shaded) with fire ellipse and major axis (blue), search centers (purple squares), search radials (shown every 5 deg, gray dashed), including selected radials (red, magenta, and cyan). The small black dots indicate fire points from previous time steps, while the large black squares indicate local maxima along search radials at this time (i.e., the current active fire points). The open black circles indicate the “back edge” of the combustion zone (see text). The identification of local reflectivity maxima (red triangles, corresponding to black squares in panel (a)) along the search radials are shown in (b)–(d) with colors corresponding to the lines in (a). Also shown in (b)–(d) are the leading edges of the fire front (green triangles).
Step 4. Local reflectivity maxima along each radial are determined using the “findpeaks” function in MATLAB (https://www.mathworks.com/help/signal/ref/findpeaks.html, last accessed November 1, 2021), which locates local maxima using a peak threshold (\(dbZ_x\)), peak prominence (\(dbZ_{pr}\)), and peak separation distance (\(sd\)). The choice of these thresholds is discussed below. The algorithm finds up to two peaks and selects the largest to estimate the fire point (\(x_p, y_p\)). Secondary peaks are stored as potential spot fire locations (\(x_{sp}, y_{sp}\)). We also identify a “back edge” point (\(x_b, y_b\)), which is the first point along the radial dropping below 90% of the reflectivity peak, provided the peak is above 40 dbZ. This point is used to capture the breadth of the region actively combusting in the most intense portions of the head fire. Examples of the peak detection (red triangles) and the “back edge” point (green triangles) are shown in Figures 3b–3d.

The results presented in this manuscript are based on threshold values of \(dbZ_x = 30\) dbZ, \(dbZ_{pr} = 5\) dbZ, \(sd = 500\) m. The sensitivity to these values was examined using 27 threshold permutations (\(dbZ_x = 25, 30, 35\) dbZ, \(dbZ_{pr} = 5, 8, 12\) dbZ, \(sd = 500, 1000, 1500\) m). These threshold combinations yield qualitatively similar results at a benchmark time (1845 UTC on 8 November 2018) when high-resolution IR data from L8 are available (see Text S1 and Figures S1–S4). The key differences are fewer fire detection points (\(x_p, y_p\)) for larger threshold values and fewer spot fires for larger prominence thresholds. The similarities among these permutations (Figure S4) suggest that the fundamental aspects of the tracking algorithm are minimally sensitive to the range of examined thresholds though future work with additional validation data sets is warranted.

Step 5. Once fire points (\(x_p, y_p\)) are estimated for all search radials centered on the three search points (up to 2160 points per time step), we refine the data by eliminating fire points with fewer than 15 previous and current fire perimeter points within a 5-km radius. This removes fire points that are separated from the quasi-continuous fire perimeter that occurs due to small spot fires or spurious peaks in the reflectivity data, which can occur due to a variety of reasons (e.g., suppression aircraft yielding reflectivity maxima). These eliminated points are, however, preserved as potential spot fires (\(x_{sp}, y_{sp}\)) but are not included in the polygon perimeter estimate (next step). Note in Figure 3a, there are three cyan squares (nearly on top of one another) indicating points that were removed in this process.

Step 6. The remaining data points (\(x_p, y_p\)) are added to a “point cloud” of all previous fire detections. These points are shown in Figure 3a as the scattered black squares. A polygon is then fit to the perimeter of the point cloud using MATLAB’s “boundary” function with a default shrink factor of 0.5 (values can range from 0 to 1 with 0 providing the convex hull and 1 providing the most compact polygon possible). Since the resulting polygon (\(x_{perim}, y_{perim}\)) encompasses the current and previous fire points, it is an estimate of the fire perimeter and can only grow in time. An example of this polygon is shown as the light gray line in Figure 3a, and we note that this perimeter does not include spot fire or back edge data points.

Step 7. From here, we loop back to step 1, once again estimating the perimeter polygon’s major axis by fitting an ellipse to the perimeter points (\(x_{perim}, y_{perim}\)) and then determining the three search points for the next time step.

3.4. Rate-of-Spread Estimation

The radar-derived fire perimeters enable estimation of the fire’s ROS. This is accomplished by constructing a continuous \(x, y, time\) \((t)\) surface from perimeter polygons. A Cartesian spatial grid of 250 m (\(x_{grid}, y_{grid}\)) is used, and we once again create a Delaunay triangulated interpolant of the form:

\[
V = f(x_{perim}, y_{perim}, time)
\]

\[
TOA = V(x_{grid}, y_{grid})
\]

where the resulting time-of-arrival (TOA) surface is analogous to the “level sets” produced in numerical fire-spread codes (e.g., WRF-FIRE, Coen et al., 2013). The TOA surface is then smoothed using a 5 × 5 median filter.
to reduce complexities in the perimeter shape before estimating ROS. ROS is computed by finding the distance between fire isochrones at 15-min intervals. This is accomplished by searching along line segments normal to the fire perimeter until the next perimeter is encountered (Johnston et al., 2018; Paugam et al., 2012). This approach assumes that the fire is moving outward from each point along the perimeter. The computed ROS captures both the spread through surface fuels and via long-range spotting events (i.e., multi-kilometer ember transport, Potter, 2016), which yields very large ROS values. The forward ROS is subsequently defined as the upper quartile (>75%) of ROS values along the entire perimeter at each time, which captures the most rapidly expanding portion of the fire at each interval.

3.5. Infrared Validation and Benchmark Data

Four sources of IR data are used to compare with our radar perimeters. These are (a) L8 IR, (b) VIIRS fire detections, (c) GOES17 4 μm brightness temperature, and (d) NIROPs perimeters. The spatial resolutions of these data sets are 30, 375, 2, and ~10 m, respectively. L8 data are only available at 1045 UTC on 8 November 2018 during the Camp fire and thus provide an excellent validation point, but exclude information about fire spread. The VIIRS data are available daily at ~2130 UTC, and the GOES17 data are available at 5-min intervals. NIROPS data are available at 0154 UTC on 9 November 2018 for the Camp fire and 2230 UTC on 9 September 2020 during the Bear fire. Note that there are no NIROPS data for the Bear Fire on the day of the radar analysis (8 November) due to mechanical issues with the aircraft.

In addition to IR data, we use data detailing the time and location of vegetation, structure, and spot fires as compiled in a publicly available National Institute of Standards (NIST) report, which summarizes the spread of the Camp Fire (Maranghides et al., 2021). The underlying data sources include civilian and fire-fighter photographs and 911 reports. From this data set, we extract the times and locations of all reported fires to compare with the radar-estimated fire perimeter.

4. Fire-Tracking Case Studies

In this section, we examine the performance of, and insights from, the radar perimeter tracking for the Camp and Bear Fires. For each case, we summarize the fire's meteorological drivers and radar-derived progression and ask the question how well does the radar-derived perimeter agree with available IR observations?

4.1. Camp Fire

The Camp Fire was ignited due to an electrical transmission line failure at ~1430 UTC on 8 November 2020 near Pulga, CA. The fire grew rapidly under the influence of a strong downslope windstorm that generated near-surface winds of 20–25 m s\(^{-1}\) (Figure 4a) from Northeast (Figure 4). Accordingly, the fire spread rapidly from northeast to southwest, burning through Paradise, CA. It went on to become the deadliest and most destructive wildfire in California history, leading to 85 fatalities, destroying more than 18,000 homes and structures, and burning 153,336 acres. The evacuation of ~50,000 people from Paradise and adjacent communities was complicated by the rapid fire spread and is a leading motivation to provide near-real-time estimates of fire spread from radar observations, such as those shown below.

The radar-derived fire progression (Figure 5, which spans multiple pages) reveals the rapid growth of the Camp Fire from shortly after its ignition up to its arrival in Paradise, CA. An animation of this progression is also available in S1. Each panel in Figure 5 shows the radar reflectivity (shaded), the current time step's fire detections (large filled black squares), potential spot fires (open squares), all previous fire detections (small black squares), and the eastern edge of Paradise (black-dashed line). Taken as a sequence, these radar data show rapid along-wind progression (NE-SW), some terrain-driven growth to the north (Figures 5c–5e), and a number of jumps in the location of the head fire indicative of long-range spotting. For example, between 1550 and 1620 UTC (Figures 5c–5f), the radar-indicated head fire “jumps” 3–4 km to the west-southwest.

Jumps in the location of the head fire continue up until 1656 UTC, when the main fire front becomes established in Paradise (Figures 5g–5i). This is consistent with 911 calls and photographic evidence in the NIST report
(Maranghides et al., 2021), indicating the main fire front arriving at ~1645 UTC, with numerous spot fires prior to that time. From this time forward, a well-developed fire front is evidenced by the high radar reflectivity and continuous north-south-oriented radar-derived head fire detections (Figures 5i–5r).
The accuracy of the radar perimeter is first established at 1845 UTC by comparing with IR perimeter derived from L8 (Figure 6, see also Figure 1). The radar-derived perimeter (light gray line) shows good qualitative and quantitative agreement with the L8 data. To be specific, both perimeter estimates provide similarly shaped and sized (82.4 vs. 82.5 km²) polygons for the main core of the fire. The polygon similarity, given by

$$\text{Similarity} = 1 - \frac{\text{area}(P1 \cup P2) - \text{area}(P1 \cap P2)}{\text{area}(P1 \cup P2)}$$

where $P1$ and $P2$ are the radar and L8 polygons, is 76% indicating a good overlap in the polygon representation of the fire's footprint, excluding spot fires (i.e., comparing only the largest L8 polygon with the radar data). Importantly, the radar data indicate similar nuances in the fire's shape, including the southward extension of the head fire near −122.575/39.73. Appendix 1 also contains a detailed assessment of polygon similarity (71%–75%) for all 27 threshold permutations at this time.

Figure 5. Radar-derived fire progression during the early growth of the Camp Fire from 1500 to 1832 UTC. Note this figure spans multiple pages. Each panel shows the radar reflectivity (shaded), the current fire perimeter estimates (solid black squares), previous perimeter points (small black squares), and a meridian indicating the eastern edge of the town of Paradise, CA.
There is also good agreement in the location of major spot fires. L8 indicates a large spot fire ∼4 km west of the primary fire front (−121.65/39.74). A grouping of radar “secondary maxima” (open black triangles) falls within this spot fire and corresponds to an obvious increase in the radar reflectivity in the vicinity (see also Figure 1b). L8 also indicates numerous smaller spot fires within ∼2 km of the fire front. These points mostly fall within the “back edge” of the radar data (open black circles), which approximate the breadth of the combusting region. The NIST-reported fires (yellow squares) provide further evidence for the fidelity of these radar estimates though some of the fires fall just outside of the radar-estimated combustion region.

Additional error statistics for the radar-estimated perimeter are obtained by computing the distribution of the minimum distances between each point along the radar perimeter (light gray line, Figure 6) and the L8 polygons as shown in the inset histogram in Figure 6. The minimum distance is the shortest Euclidian distance between a given radar-estimated point and the vertices of all the L8 IR polygons, including the numerous spot fires. Negative (positive) distances indicate radar points falling outside (inside) the L8 polygons. These data show that the
distribution of error is quasi-Gaussian, roughly centered on zero (mean of $-50\, m$), and has a standard deviation of 386 m. These statistics demonstrate how, in the future, uncertainty bounds for the radar perimeters can be established, especially if these data are to be assimilated into numerical models (e.g., WRF-SFIRE).

The continual growth of the Camp Fire is examined in Figure 7, revealing complex progression through Paradise, including the combustion of 1000s of homes and structures. During this time, the fire develops three distinct high-reflectivity cores linked to the northern, central, and southern portions of the advancing fire front. Each core appears to be linked to both spotting and localized fire progression. Despite these complexities, a comparison with VIIRS fire detections at 2130 UTC indicates good agreement (Figure 8). The best agreement is in the main body of the fire with less agreement along the southwest flank of the advancing fire. In this region, the radar data indicate possible spot fires and a “back edge” of the combustion zone, but no continuous fire perimeter. NIST

Figure 5. (Continued)
data indicate confirmed spot and structure fires in this region. It should be noted that some of the VIIRS detections may suffer from “hot plume” contamination.

After 2130 UTC, the fire continues rapidly to the southwest. To summarize this portion of the fire spread and the fire evolution as a whole, we compare the aggregated radar “point cloud” with a NIROPS perimeter obtained at 0154 UTC (1754 PST; Figure 9). The agreement for most of the fire perimeters is striking with radar-detected points filling most of the IR perimeters, including lobes and nuances in the fire shape. There are some discrepancies over the NW portion of the fire, but only a scattering of radar-estimated points falls outside of the IR perimeter, which is after ∼20 hr of unsupervised tracking by the radar algorithm. The polygon similarity is ∼83%, which exceeds the similarity at earlier times, underscoring the potential utility of our approach.

The radar-derived time-of-arrival (TOA) surface and ROS vectors for the period of 1530-0130 UTC are shown in Figures 10a and 10b. An accompanying time series (Figure 10c) shows the temporal distribution of forward ROSs along the perimeter (i.e., the upper quartile of ROS for the perimeter as a whole). Taken together, these data indicate maximum forward ROSs of 1–3.5 m s$^{-1}$ early in the fire's growth. These large forward ROSs are an order of magnitude larger than in most fires (Gould & Sullivan, 2020) and exceed those reported for a selection of crown fires in (e.g., maximum of about ∼1 m s$^{-1}$ in Alexander & Cruz, 2006). We also place the observed ROS in the context of the ambient wind speed and gusts (black- and red-dashed lines, respectively) from a nearby weather...
station (PG131, location shown in Figure 3a) to examine the applicability of the “10% rule” proposed by Cruz and Alexander (2019), wherein a fire's forward ROS is approximated as 10% of the ambient wind (in any unit). During the early growth of the fire, the ROS is as much as 6 times greater than the 10% rule, whereas later the ROS roughly corresponds with 10% of the wind speed and gusts. As suggested in the radar snapshots, the rapid early growth is due, in part, to long-range spotting, which drives the fire forward as much as 3 km in just 15 min. We also note that in a macroscopic sense, the fire traveled ~12 km from its origin at ~1430 UTC to Paradise at ~1645 UTC (see NIST report), implying an impressive bulk ROS of ~1.2 m s⁻¹.

In summary, the radar perimeter estimates for the Camp Fire agree well with IR snapshots at three intervals and provide insights into the fire's progression. This good performance suggests that radar tracking can provide
4.2. Bear Fire

The Bear fire began among a collection of lightning fires on 17 August 2020 (called the North Complex), then on 8 September, after weeks of slow progression jumped the Middle Fork of the Feather River and embarked on a rapid downhill run toward Lake Oroville, consuming an estimated 150,000 acres by the following morning. Much like the Camp Fire, the fire’s growth was driven by strong northeasterly downslope winds (Figure 11a). The sustained surface winds were as strong as 15 m s\(^{-1}\) (Figures 11a and 11b) with gusts up to 22 m s\(^{-1}\) (Figure 11b) as reported at station PG326 (see location in Figure 3a).

The radar-derived fire perimeters during the Bear Fire, shown in Figure 12, and subsampled in 30 min intervals, revealing rapid along-wind southwesterly growth, including substantial spotting. A corresponding animation is available in S2. Spotting is evident in the 2101 and 2131 UTC snapshots (Figures 12d and 12e) and contributes to multi-kilometer forward spread of the head fire in short periods of time, such as was also observed during the Camp Fire. The narrow parabolic shape of the head fire is characteristic of rapidly advancing fires (Anderson, 1983) and the high-reflectivity values represent intense combustion (and thus, lofting of pyrometeors) in the head fire (McCarthy et al., 2019).

Figure 8. Comparison of radar-derived and Visible Infrared Imaging Radiometer Suite (VIIRS) fire observations at 2126 UTC. Shown are the radar reflectivity (shaded), current radar-estimated fire perimeter points (large, solid black squares), “back-edge” radar-estimated fire perimeter (open black circles), spot fires (open black squares), and previous fire perimeter points (small black squares). Also shown is the polygon fit to the radar detections (gray line) and the VIIRS active fire pixels (magenta diamonds). National Institute of Standards reported spot, structure, and vegetation fires are shown in yellow.
The radar perimeters are compared with VIIRS and GOES17 data at 2206 UTC as shown in Figure 13. The radar-estimated points and perimeter fall within the GOES17 IR footprint (background shading Figure 13b), which is typically overestimated due to the 2-km pixel resolution. The VIIRS fire detections (magenta squares) mostly agree with the radar detections though there are several spurious VIIRS fire detections due to “hot plume” and other unknown error sources occurring to the south of the fire. For example, there is a collection of pixels southeast of the fire that is clearly spurious and falls outside of even the final fire perimeter (see Figure 3). We do not compute a polygon similarity for these data since the sensor resolutions are so different and due to the spurious VIIRS detections. The qualitative agreement is, however, notable.

Figure 14 shows the continued radar-estimated fire progression and radar reflectivity. Like the previous sequence, rapid along-wind growth to the southwest is apparent. However, during this time, the fire transitions from a narrow parabolic nose to a broader, blunter head fire, and then to a period where the progression along the flanks of the head fire is faster than the progression in the center of the head fire, causing a “folding over” of the fire shape (i.e., an inverted parabola). The physical processes driving this transition are linked to a region of strong flow reversal (i.e., a fire-generated wind opposing the mean wind), strong wind shear, and vortex generation as described in Lareau et al. (2022). The pyrometeor laden vortex is particularly apparent as the localized radar reflectivity maxima and fire points at 0125 UTC (Figure 14e) near −121.2/39.65.

The tendency for the fire to progress most rapidly along the flanks of the head fire continued up through 0500 UTC as shown in both the radar data and GOES17 IR brightness temperature (Figures 15a–15d). After that time, winds shifted to the south and opened the northern flank of the fire causing spread to the north, which is captured by both GOES17 and the radar estimates between 0657 and 0757 UTC (Figures 15e–15h). While high-resolution validation data are not available for this case due to the lack of a nighttime IR flight (due to a mechanical issue with the aircraft), we note that the radar detections fall neatly within the GOES17 IR footprint throughout the fire's evolution.
As with the Camp Fire, we conclude this section with an ROS analysis, shown in Figure 16. The TOA surface and ROS vectors are shown for the 1900–0400 UTC period, which include the initial rapid fire growth and the subsequent “folding over” of the fire perimeter. The maximum ROS is 1–3 m s\(^{-1}\), which is similar to that during the Camp Fire, and again likely indicates long-range spotting due to ember transport through the plume. The time series of forward ROS and nearby wind speed data (Figure 16c) indicate that the ROS only loosely agrees with the “10% rule.”
5. Application to Other Fires

While we have demonstrated the radar-tracking approach for two geographically and meteorologically similar fires, a natural question is, “how well does the proposed approach perform for fires observed from different
NEXRAD sites and with different meteorology? To address this question, we include two summary analyses of other fires, the King (Figure 17a) and Caldor Fires (Figure 17b), both observed with the Sacramento, CA (KDAX) radar (Table 1). These fires differ than the Camp and Bear fires in that their progression was driven by typical southwest and west upslope winds in the Sierra Nevada as opposed to strong downslope northeasterly winds. In addition, both fire's produced deep, more-upright, pyrocumulus-topped convective columns (see Figure 13 in Peterson et al., 2017). In the case of the King Fire, fire-induced winds are also thought to have substantially contributed to the fire's rate and direction of spread (Coen et al., 2018; Lareau et al., 2022). These fires are also at a much larger range from the radar site (∼110 km vs. 30–45 km), yielding a lower beam-to-beam azimuthal resolution (Table 1), and experience spread in directions both along and across scans. Despite these geometric and meteorological differences, the summary data in Figure 16 indicate that the radar tracking algorithm produces fire

Figure 12. Radar-derived fire progression during the Bear Fire from 1925 to 2151 UTC on 8 September 2020. Each panel shows the radar reflectivity (shaded), the current fire perimeter estimates (solid black squares), and previous perimeter points (small black squares).
rate and direction of spread consistent with the available IR aircraft observations and thus retains its potential to provide timely and reliable tracking of these fires.

6. Summary and Outlook

We have developed, presented, and validated a radar-derived fire-perimeter tracking method that produces accurate fire-perimeter estimates as compared to available IR data. The fire-tracking algorithm is based on the simple insight that local maxima in the radar reflectivity tend to occur above the head and flanking fire. During the Camp Fire, the radar-derived perimeters agree well (76%–80% polygon similarity) with a fortuitous L8 overpass and a NIROPs IR perimeter. The radar perimeters also agree well with VIIRS and GOES17 fire perimeter estimates during both the Camp and Bear Fires, indicating that this approach can provide important tactical information in operational settings (e.g., among Incident Meteorologist, Emergency Managers, Fire Chiefs, etc.).

There are both strengths and weaknesses to the radar-based perimeter tracking. Among the strengths are (a) the operational availability of NEXRAD observations at high temporal and spatial resolution, and (b) the ability of radars to observe fire processes even during periods of dense smoke and cloud cover (including pyroCb), which can obscure satellite observations and preclude aircraft observations. For example, in the present study, the radar data provide critical details of fire progression during the Camp Fire's run into Paradise that were otherwise unavailable due course satellite data (GOES) and weather conditions that precluded aircraft operations. An additional strength of the radar observations is that they contain more information than we have highlighted in this study, including information about plume height, plume geometry, plume microphysics, pyroCb initiation, and fire induced winds (e.g., Lareau et al., 2018, 2022). As such, a more comprehensive use of radar observations for fire situational awareness is warranted as is further investigation of how to best extract information about fires from these data. This work is ongoing.

Some of the weaknesses of the approach are as follows. At a fundamental level, radars do not directly measure the fire, but instead the pyrometeors produced by fires. This can lead to mismatch between the radar maxima and the fire perimeter due to drift of the plume, an issue that becomes more problematic for fires at long ranges from the radar since the beam height is far above the surface. The fires analyzed here do not suffer from this problem because the scan angle “skims” the ground, but in other locations (especially in remote regions), the technique may work not as well as in the cases presented here. Fortunately, for many of the at-risk population centers in the western US, there is good NEXRAD coverage. Other limitations include the lack of radar scatterers for low-intensity fire, especially at night, though the primary use case of the proposed approach is to track high-impact large
Figure 14. Radar-derived fire progression during the Bear Fire from 2230 to 0225 UTC. Each panel shows the radar reflectivity (shaded), the current fire perimeter estimates (solid black squares), and previous perimeter points (small black squares).
Figure 15. Comparison between radar-derived GOES17 fire observations during the Bear Fire (a,c,e,g) Radar reflectivity (shaded), current radar-estimated fire perimeter points (large, solid black squares), “back-edge” radar-estimated fire perimeter (open black circles), spot fires (open black squares), and previous fire perimeter points (small black squares) (b,d,g,h) Radar points as before, along with GOES17 4-μm brightness temperature shaded in the background. GOES-17 data are the maximum pixel temperature for the period starting at 1800 UTC and ending at the analysis time (displayed in each panel).
wildfires in near-real time, which are likely to produce ample radar scatters, and thus be well observed. Finally, there is a pressing need for better validation data. In the present study, we leverage one advantageous satellite overpass to provide high-resolution validation, but in the future, we hope to provide more extensive validation and error quantification using sporadically available aircraft IR, or, ideally, field campaign observations with collocated instrumentation. Such data would facilitate better perimeter skill score quantification (e.g., Skok & Roberts, 2016) and fire ROS estimation and validation (e.g., Zhang et al., 2019).

In addition to the potential operational utility of radar-based perimeter tracking, the subsequent time-of-arrival surfaces and fire perimeters can, and should, be used to drive coupled fire-atmosphere models (e.g., WRF-SFIRE). In doing so, we may be able to bypass uncertainties in semiempirical fire-spread codes (e.g., Rothermel, 1972), forcing models to the observed perimeter and thus rendering more accurate short-term fore-

Figure 16. Overview of the rate-of-spread computed from radar-estimated perimeters. (a) Perimeters and spread vectors with color bar indicating the time. Vector scaling is included in the top-left corner. (b) Time-of-arrival surface, (c) time series showing the distribution of rate of spread along the perimeter, including the median (red), interquartile range (solid black), and 5%–100% interval (gray). Also shown are the wind speed and wind gust observations from PG326, scaled by 0.1.
casts for fire spread. Such data could be used in “nowcasting” of fire spread. To better realize the nowcasting potential of these data, future research incorporating additional radar parameters (e.g., polarimetric observations), knowledge of fuel distributions, and the aforementioned quantification of errors relative to available IR data should be considered.

Conflict of Interest
The authors declare no conflicts of interest relevant to this study.

Data Availability Statement
NEXRAD and GOES-17 data can be obtained from the Amazon cloud at https://registry.opendata.aws/noaa-nexrad/ (NEXRAD on AWS, 2021) and https://registry.opendata.aws/noaa-goes/ (last accessed for both links 1 November 2021) (NOAA Geostationary Operational Environmental Satellites 16 & 17, 2021). NEXRAD data files can be converted to the NETCDF format using the National Oceanographic and Atmospheric Administration’s (NOAA) Weather and Climate Toolkit, which are freely available at https://www.ncdc.noaa.gov/wct/ (last accessed 1 November 2021) (NOAA’s Weather and Climate Toolkit, 2021). High-Resolution Rapid Refresh (HRRR) meteorological data can be accessed via the University of Utah archive (https://doi.org/10.7278/S5JQ0Z5B) described in Blaylock et al. (2017). Fire perimeter data are available at https://ftp.wildfire.gov (last accessed 1 November 2021). Archived VIIRS data are available at https://firms.modaps.eosdis.nasa.gov/download/ (last accessed 1 November 2021) (NASA’s Fire Information for Resource Management System, 2021). The MATLAB software and toolboxes (image processing and signal processing) needed to reproduce our results are commercially available from MathWorks® (MATLAB, 2018). The code used to generate the results is available under a BSD 3-Clause License at https://github.com/nplareau/Tracking_Wildfires_with_Weather_Radar (Lareau, 2022, https://doi.org/10.5281/zenodo.6471997), which contains both a radar preprocessing code (NEXRAD_PREPROCESSOR.m) and a perimeter-tracking code (radar_perimeters_v1.m).
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