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Towards the use of Remote Sensing for Identification of Building Damage, Destruction, and Defensive Actions at Wildland-Urban Interface Fires

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Abstract. Post-fire remote sensing provides a promising tool for assessing building damage, destruction, and defensive actions from wildland fire. However, limited studies exist to guide image acquisitions. Consequently, we compare remotely piloted aircraft systems and satellite post-fire imagery to ground-based assessments from the 2017 California Tubbs Fire to classify building damage, destruction, and defensive actions in an intermix and interface community. We also geolocate defensive action information from active fire images, videos, and eyewitness accounts. We utilize both manual and object-based classification approaches. Both types of overhead imagery using manual classifications had high kappa statistics ranging from 0.81 to 0.96, indicating almost perfect agreement with ground-based assessments for primary building destruction (e.g., homes). Object-based classifications of destruction had kappa statistics ranging from 0.63 to 0.88 for primary buildings, indicating substantial agreement. Additionally, manual and object-based classifications identified many destroyed secondary buildings (e.g., sheds) missed by ground-based assessments. Occlusions due to canopy cover contribute to lower classification results in the intermix community. All imagery missed significant damage identified in the ground-based assessment. Remotely piloted aircraft systems imagery was superior to satellite imagery in identifying defensive action indicators. Nonetheless, all image types are valuable additions to ground-based assessments of damage, destruction, and defensive actions. Finally, we demonstrate the importance of accounting for defensive actions in assessing building response at wildland-urban interface fires.

Keywords: Wildland-Urban interface, WUI, Wildland Fire, Remote sensing, Tubbs fire, Light detection and ranging

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1. Introduction

The number of buildings destroyed due to wildland fires continues to increase. The 2017 California Tubbs Fire (Tubbs Fire) saw the most destroyed buildings (over 5,000) from any Wildland-Urban Interface (WUI) fire at the time, only to be surpassed in 2018 by the California Camp Fire, which destroyed over 18,000 buildings [1]. Currently, we face the challenge of WUI fires during disease pandemics [2], a world of diminishing resources, social unrest, and other challenging conditions. Therefore, the need to respond quickly, safely, and virtually to damage and destruction from WUI incidents is a pressing concern.

However, accurately documenting building damage and destruction can be challenging in a post-fire environment. For example, consider the following ground-based reports on buildings affected by the Tubbs Fire. The "Tubbs Fire Watershed Emergency Response Team Final Report" [3] states that the Tubbs Fire destroyed 7,010 buildings and damaged 487. The geographic information system (GIS) dataset of destroyed buildings from Sonoma County [4], containing damage assessments from the California Department of Forestry and Fire (CAL FIRE), has 6583 buildings documented as destroyed and 429 damaged buildings. CAL FIRE [5] also lists 5636 buildings as destroyed and 317 damaged buildings. The County of Sonoma [6] lists 6686 buildings, 112 barns, over 80 commercial buildings, 37 school buildings, and a church as destroyed.

The above discrepancies in reported building damage and destruction highlight the difficulty in performing post-fire assessments from the ground alone, particularly for a significant incident. The discrepancies also point out that there is no standard approach for post-fire assessments of building destruction and damage. For example, it appears that sometimes sheds and other secondary buildings are documented more thoroughly than other times. This difference in assessments could be due to the need to rapidly identify primary buildings (e.g., homes) destruction, focusing on buildings greater than 11.15 m^2 (120 ft^2). Finally, lacking in all these assessments is data that characterizes the specific building damage (e.g., damaged roof, damaged deck, or damaged fence). Maranghides et al. [7] recommended collecting specific building damage information to identify building vulnerabilities.

Post-fire remote sensing can provide a rapid, safe, consistent, and effective means to aid in deriving estimates of damage, destruction, and defensive actions at WUI incidents [8]. Object-based image classification for rapidly identifying building destruction and defensive actions showed significant promise at the 2012 Colorado Waldo Canyon Fire [8]. Additionally, it is becoming more prevalent for large WUI fires to have publicly available post-fire imagery to help identify building damage and destruction e.g., [[9], [10] and [11]].

Classifying defensive actions from remote sensing data can aid research into the role of defensive actions on overall building response during WUI fires [8]. Furthermore, crowdsourcing from social media, internet images, videos, and other public sources provides additional means to identify defensive actions and timelines of burning features while providing further details about the fire. When integrated, ground and aerial datasets can provide information beyond what either can give individually.

Additionally, few studies attempt to account for the influence of defensive actions on building response. However, a growing body of evidence portrays the importance of considering defensive actions in assessing building response e.g., [8, 12, 13, 14 and 15]. It is essential to consider defensive actions in post-fire WUI assessments because they alter exposure to heat fluxes (from flames and embers) experienced by nearby buildings. Such exposure is critical to consider when evaluating building response e.g., [7, 13].

Despite the potential for remote sensing to further our understanding of WUI incidents, few studies have assessed the potential of remote sensing for identifying building damage and destruction. To our knowledge, only one study examined the use of remote sensing to identify defensive actions [8]. Maranghides et al. [16] also showed that identifying secondary building destruction required the combined use of post-fire field assessments and pre-fire imagery. The Regional Municipality of Wood Buffalo [17] utilized post-fire imagery in the 2016 Canadian Horse River Fire. Also, Ahmed et al. [18] employed remote sensing of satellite data to assess structural damages from the 2016 Canadian Horse River Fire.

This study uses the Tubbs Fire incident to build on the limited research to date to assess the use of remote sensing for building damage, destruction, and defensive actions. Here we utilize the unique combination of imagery from remotely piloted aircraft systems (RPAS), satellites, and ground sensors to answer the following questions:

1. How do assessments of building damage using visual classifications of satellite imagery, visual classifications of RPAS imagery, and ground-based observations compare to each other?
2. How do assessments of building destruction using the automatic classification of satellite imagery (satellite object-based classification) and automatic classification of RPAS imagery (RPAS object-based classification) compare with results from visual classifications and ground-based observations?
3. Is building survival dependent on the presence of defensive actions on nearby buildings and properties? Here, we identify defensive actions by visually classifying overhead imagery and ground-based imagery and observations.

Consideration of the above questions builds on the work conducted by McNamara et al. [8] through testing the same methods in different environments with satellite and RPAS acquired imagery. As such, these evaluations provide new information about the benefits and shortcomings of remote sensing platforms (i.e., RPAS and satellite-based) and spatial resolutions for WUI post-fire building assessments. Additionally, through the above evaluations, we add to the findings of McNamara et al. [8] and others e.g., [7 and 13] regarding the importance of accounting for defensive actions, both close to and some distance from affected buildings, when evaluating building response.

2. Methods

2.1. Study Site

The Tubbs Fire started on the evening of October 8, 2017, traveling over 29 km (km) in 3.25 h [19] driven by Diablo Winds. Containment occurred on October 31, 2017, after a total of 36,807 acres burned in Sonoma and Napa Counties, resulting in the death of twenty-two people [3]. Winds were initially 18 m s^{-1} with gusts up to 35 m s^{-1}[20] when most building destruction occurred. The fire jumped the 101 freeway, a six-lane highway, and entered densely populated suburban and urban areas in Santa Rosa [20].

In this effort, we utilized the input data shown in Tables 1 and 2 in two study sites (Fig. 1) to classify building damage, destruction, and defensive actions. The Tubbs Fire did not see the collection of RPAS imagery throughout the fire. Therefore, we compared the RPAS imagery (contains 2042 buildings) and satellite imagery (contains 3402 buildings) from Coffey Park (Table 1), an interface community with a high density of buildings (Fig. 1), to building damage, destruction, and defensive actions identified from the ground-based assessment (dataset two in Table 1). Because the satellite imagery covered a more considerable extent, we also expanded the assessment for satellite imagery to other suburban and urban areas surrounding Coffey Park, resulting in more buildings assessed with the satellite imagery.

To examine the use of satellite imagery for forested communities, we also assessed the techniques utilized here in an intermix study site, consisting of lower-density buildings (617 buildings) and more vegetation (Fig. 1). In both study sites, we included areas outside the final fire perimeter. This inclusion of buildings outside the fire perimeter represented a realistic post-fire scenario where damage assessors do not know the fire's exact extent immediately after the fire.

We chose the Coffey Park study site because it contained post-fire RPAS imagery, satellite imagery, the most building destruction of any high-density communities, and a mix of residential and commercial buildings. The intermix study area was selected based on watershed boundaries and coincided roughly with the Upper Mark West Creek Watershed. We selected this watershed over other watersheds to the south because there was a more even distribution of destroyed and surviving buildings. The building density was also lower in this area compared to other potential sites.

2.2. Classifications and Accuracy Assessments

We utilized pre-fire building footprints derived from Light Detection and Ranging (LiDAR) data in both study sites and all object-based classifications. The Sonoma County Vegetation Mapping and LiDAR Program [20] created building footprints using the "Vectorize Buildings" tool in MicroStation™. This approach is similar to that utilized by McNamara et al. [8] in that both techniques automatically or semi-automatically extract building footprints from LiDAR point clouds. We also digitized missed or new building footprints to add to the initial building footprint

Table 1
Pre-Fire and Post-Fire Datasets used in this Study

Data source	Characteristics	Data use
1. CAL FIRE Damage Assessment 2017 [4]	Last Update: October 26, 2017 Spatial Resolution: Building Center Point	Portray destroyed and damaged buildings at the Tubbs Fire from a ground-based assessment
2. Cartographic Building Footprints – File Geodatabase [22]	Last Update: April 22, 2014 Spatial Resolution: Polygon Dataset of Building Footprints	Segment post-fire overhead images to only include buildings. We added new and missed buildings from datasets three, four, five, seven, eight, and nine in this table
3. MAXAR WorldView-3 Satellite [11]	Acquisition Date: 10/17/2017 Spatial Resolution: 0.46 m Spectral Resolution: 3-Band (Red, Green, Blue)	Perform object-based classification of destruction and visual classification of damage, destruction, and defensive actions. Identify buildings missed in Sonoma County Vegetation Mapping and LiDAR Program [20]
4. Nadar RPAS Imagery Coffey Park Acquired by Drone Scholars working with Sonoma County and Alameda County Sheriff's Office [10]	Acquisition Date: October 2017 (Exact Date Unknown) Spatial Resolution: 0.02 m Spectral Resolution: 3-Band (Red, Green, Blue)	Perform object-based classification of destruction and visual classification of damage, destruction, and defensive actions. Identify buildings missed in Sonoma County Vegetation Mapping and LiDAR Program [20]
5 360° Drone Panoramics: Coffey Park [21]	Acquisition Date: October 2017 (Exact Date Unknown) Spatial Resolution: Unknown Spectral Resolution: 3-Band (Red, Green, Blue)	Perform visual classification of damage and defensive actions. Identify buildings missed in Sonoma County Vegetation Mapping and LiDAR Program [20]
6. Sonoma County Parcels—Shapefile [35]	Geographic Information System dataset of parcel boundaries	Delineate primary versus secondary properties on a single property
7. National Agriculture Imagery Program [36]	Acquisition Date: 2014 (Exact Date Unknown) Spatial Resolution: 1 m Spectral Resolution: 4-Band (Red, Green, Blue, Near Infrared)	Identify buildings missed in Sonoma County Vegetation Mapping and LiDAR Program [20]. Dataset is also used to identify locations where there were abrupt pre-fire changes in vegetation conditions

Table 1 continued

Data source	Characteristics	Data use
8. Google Earth Pre-Fire and Post-Fire Overhead Imagery	Acquisition Date: June 2017 – February 2018 Spatial Resolution: Unknown Spectral Resolution: 3-Band (Red, Green, Blue)	Identify buildings missed in Sonoma County Vegetation Mapping and LiDAR Program [20] and areas where fire cessation corresponded to vegetation changes. We used post-fire imagery to confirm the visual classification of destroyed buildings
9. Google Earth Street View Imagery	Acquisition Date: June 2017 – February 2018 Spatial Resolution: Unknown Spectral Resolution: Visible Imagery (Red, Green, Blue)	Geolocate active fire images and videos. Examine study areas for the presence of wood roofs. Identify buildings missed in Sonoma County Vegetation Mapping and LiDAR Program [20]

dataset (dataset two in Table 1) based on buildings identified in datasets three, four, five, seven, eight, and nine (Table 1).

We visually classified building footprints into primary versus secondary using datasets two, three, four, five, seven, eight, and nine (Table 1). Primary buildings represent buildings corresponding to the property's primary land use (e.g., homes on residential properties). Secondary buildings correspond to buildings that are not related to the primary land use (e.g., a shed or gazebo on the residential property). In some cases in the intermix study area, it was not easy to differentiate primary versus secondary buildings due to multiple large buildings on the parcel. Consequently, some buildings we classified as not determined.

We utilized the Sonoma County Parcels dataset (dataset six in Table 2) to identify buildings on a particular property. In the interface study area, the primary building (e.g., home) was typically more extensive in areal extent compared to secondary buildings on the respective property. However, multiple large buildings were often on a property at the intermix study site, making the primary and secondary building classifications challenging. Nonetheless, in this analysis, we included buildings for which we could not determine a primary or secondary classification because these were buildings, some of which were significant in size. Finally, in the intermix study area, we performed a bulk spatial adjustment of the building footprints by moving them about nine meters to the east to better align with the satellite imagery.

Next, we visually classified building damage and destruction using the WorldView-3 satellite imagery (dataset three in Table 1) at both study sites (Fig. 1) and the RPAS imagery (dataset four in Table 1) collected at the interface study site (Fig. 1). Visually classifying damage in the interface area also occurred using 360° RPAS Panoramics [21] (dataset five in Table 1) where available. Then, we com-

Table 2
Active Fire Datasets used in this Study

Data source	Characteristics	Data use
Tubbs fire brought Death and destruction to coffey park [25]	This article contains eyewitness accounts of a homeowner defending his property	Identify the location of defensive actions by the homeowner
Tubbs Fire: California's Most Destructive Fire in History [37]	This video contains descriptions and information on defensive actions	Identify locations of defensive actions
Firefighter perspective – Tubbs Fire Santa Rosa [33]	Video from Berkely firefighters showing the locations of Berkely Engine 6 defensive actions	Identify locations of defensive actions
Those first 24 hours [38]	Documentary focusing on first responders and community members making a response	Provides a general idea of the extent of defensive actions; the documentary, while portraying community members' actions, shows a more significant percentage of actions by trained first responders than citizens. Community member actions identified in this video appeared to be outside our study site
Santa Rosa fires: First hours of the devastating Tubbs fire in 9 min [39]	Video of fire behavior and defensive actions	Identify defensive actions locations and show flanking fire behavior along the eastern side of Coffey Park and other locations
Last October (2019) Documentary | City of Santa Rosa, CA [40]	Describes actions of City of Santa Rosa Workers and First Responders	Shows fire behavior and first responders describing the inability to "get in front of the head fire" due to the wind speeds and fire intensities and the need to evacuate lives
Santa Rosa Fire 2018 – Coffey Park at Barns Road [41]	RPAS video of Coffey Park after the destruction of the majority of homes	Identify locations of defensive actions and fire behavior
Coffey Park drone fly over… 10/10/2017 [42]	RPAS video of Coffey Park after the destruction of the majority of homes	Identify locations of defensive actions through watermarks and other indicators
Santa Rosa firestorm October 10 9 17 9 2017 [43]	Headcam video of a private citizen on a bike driving through Coffey Park	Identifies locations of defensive actions from first responders on Skyview Drive
Incredible photos show how one man's house was saved in Tubbs Fire [44]	Aerial photo showing a home defended by a homeowner using a hose provided by first responders	Identifies the location of the one confirmed defensive action by a homeowner in Coffey Park

pare these classifications against building damage and destruction from the ground-based assessments (dataset one in Table 1), representing a typical rapid assessment conducted immediately after the incident.

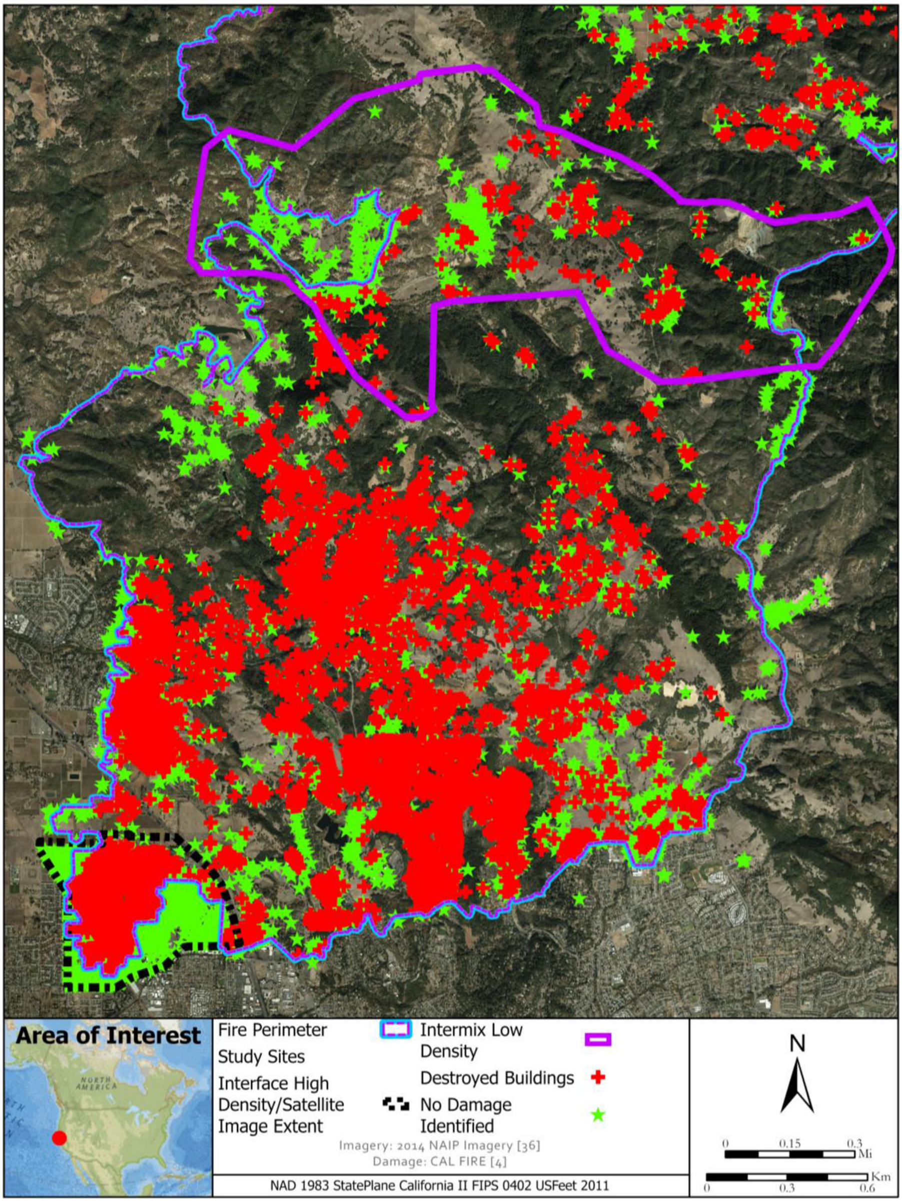


Figure 1. Tubbs Fire perimeter with destroyed and surviving buildings along with our two project study sites. Coffey Park is the interface study area in the southwest corner of the image (encompassed by a segmented black line). The intermix study area is located in the northern portion of the image (encompassed by a solid purple line).

We performed an object-based classification of the RPAS and satellite imagery for building destruction at both study sites using the approach described by McNamara et al. [8] and further detailed in the supplemental materials to this paper. The approach described by McNamara et al. [8] does not classify all destroyed areas within the building footprint, even though, in most cases, the destruction was complete within the building footprint. Consequently, as described by McNamara et al. [8] and detailed in the supplemental materials, we calculated the classified destroyed building percentage (classified destroyed percentage) to normalize the classified destroyed area across buildings. We classified a building as destroyed if the classified destroyed percentage, not the actual destroyed area, typically the entire building, is $> 50\%$.

We also implemented the machine learning functionality in Feature Analyst™. After the initial object-based classifications, we manually selected a small subset of polygons for destroyed buildings improperly classified as surviving (surviving buildings might be damaged) and a small subset of polygons that were correctly classified as destroyed. We then re-ran the classification with these errors identified using these results in the final analysis.

We used confusion matrices, the kappa statistic, and overall mapping accuracy [23] to assess all image classifications' accuracy e.g., [2]. We compared visual classifications against the ground-based assessments. We evaluated object-based classifications using the combined results from the visual classifications and ground-based assessments. The combined results included correct estimates of destruction because the ground-based assessment sometimes missed destroyed buildings. Also, the satellite visual classification sometimes incorrectly assigned destroyed buildings to the damaged category.

Finally, we visually classified RPAS and satellite imagery (datasets three and four in Table 1) for signs of defensive actions using visual indicators described by McNamara et al. [8] and shown in Fig. 2. Also, we crowdsourced videos and images of active fire defensive actions (Table 2) to further document defensive actions and validate the post-fire aerial image indicators used in this study. Additionally, we included fuel clearing (e.g., dozer or hand lines) and vegetation changes that resulted in an abrupt stop in fire spread. Some locations with an abrupt stopping of vegetative fires could be due to changes in fire behavior independent of defensive actions. However, some of these locations are also associated with other defensive action indicators (e.g., Fig. 2), providing evidence of the abrupt stopping of fire associated with defensive actions in some cases. We then assessed the effectiveness of defensive actions' in stopping fire spread at Coffey Park.

2.3. Defensive Action Effectiveness

The Coffey Park assessment of defensive action effectiveness involved dividing the buildings into (1) destroyed and damaged buildings with all their adjacent buildings destroyed and (2) destroyed and damaged buildings having at least one surviving bordering building. Further partitioning of these two groups of destroyed buildings occurred as defended versus not defended categories using the combined

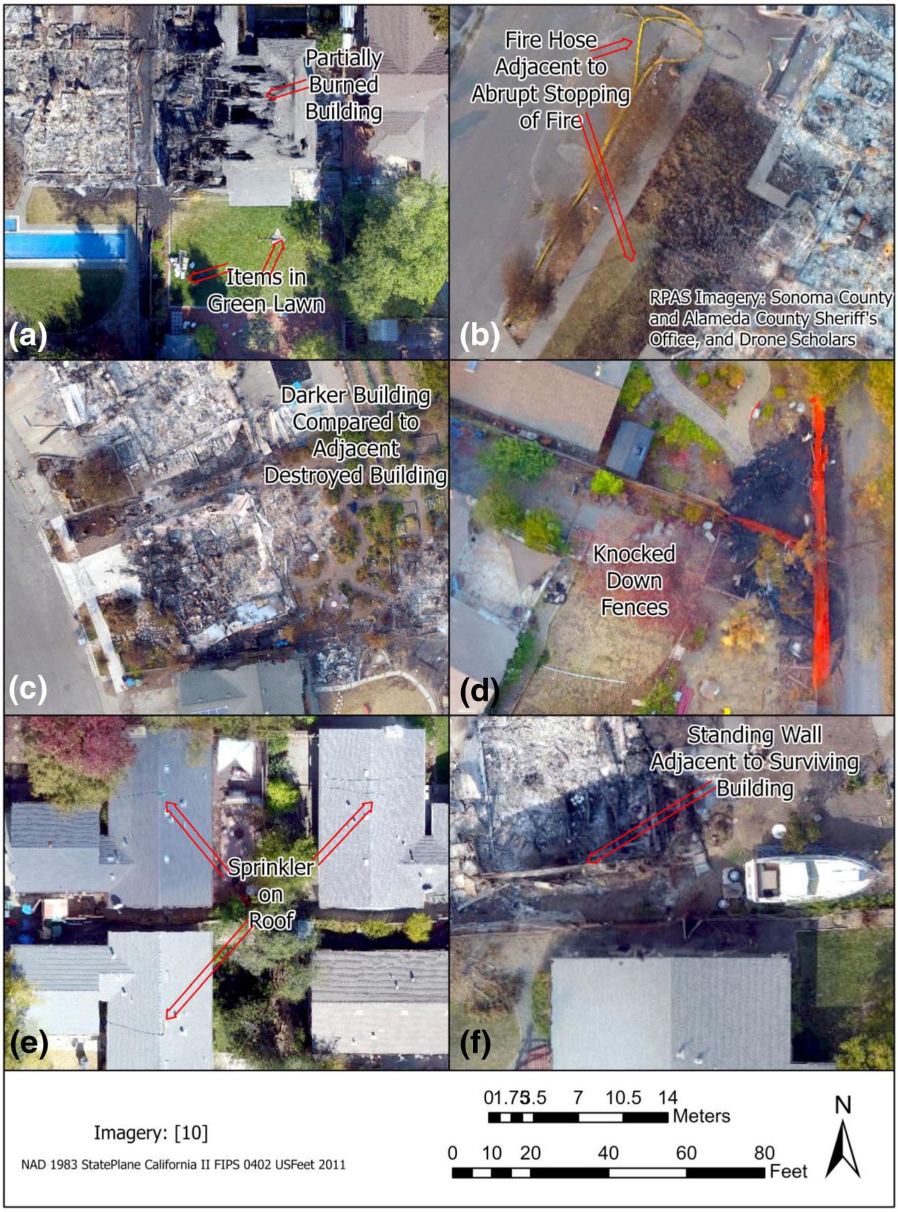


Figure 2. Visual indicators of defensive actions from the RPAS imagery [10]. The image E had a video [33] of first responders and citizens in the area. Images A, C, and F are confirmed through ground videos [39].

classifications of defensive actions from all sources (datasets three, four, and five in Table 1 and all data in Table 2).

We used these groupings of buildings to perform a Chi-square analysis to test the following hypothesis:

Hypothesis1 (H1) surviving and damaged buildings adjacent to destroyed and damaged buildings are dependent on defensive actions on the adjacent destroyed or damaged buildings or surrounding properties.

The above test is not consistently logical in the intermix study site because the property sizes vary significantly, resulting in considerable variation in distances between buildings. Nonetheless, we examined the relationship between the stopping of fire spread and signs of defensive actions in the intermix study site through visual comparison of destroyed and surviving buildings.

Defensive actions might not be the only factor contributing to the stopping of fire spread. Changes in exposure conditions, such as reduced wind, vegetation treatments not visible in the imagery, and building treatments, might affect fire spread cessation. We did not examine these other factors in this study. Nonetheless, the dependence of the ending of fire spread on defensive actions would contribute to the growing body of research that shows defensive actions to be a critical factor when assessing building response.

Table 3
Confusion Matrix Comparing RPAS [10] Visual Classification (VC) for Damage and Destruction to Ground-Based Assessment Results [4] in Coffey Park

Ground-based assessment [4]						
	Destroyed	Damaged	No damage or not assessed	Totals	Commission errors	Producer's accuracy
RPAS VC						
Destroyed	1196	0	458	1654	27.7%	72.3%
Damaged	0	5	4	9	44.4%	55.6%
No damage	0	10	369	379	2.6%	97.4%
Totals	1196	15	831	2042		
Omission errors	0%	66.7%	55.6%			Overall mapping accuracy = 76.9%
User's accuracy	100.0%	33.3%	44.4%			Kappa statistic = 0.49

3. Results

3.1. RPAS Visual Classification in Coffey Park

The RPAS visual classification accuracy in Coffey Park was 76.9%, with a kappa statistic of 0.49 (Table 3), indicating moderate agreement [24]. The ground-based assessment (Table 1) did not identify 458 buildings identified as destroyed in the RPAS visual classification. Of these, 447 were secondary buildings, and 11 were primary buildings, all of which are shown as destroyed in the RPAS visual classification and missed in the ground-based assessment (Table 1). The kappa statistic is 0.95, indicating almost perfect agreement [24], and the overall accuracy is 98.6% when considering only primary buildings.

However, there are discrepancies between damage estimates from the RPAS visual classification and the ground-based assessment for damage, as demonstrated through the high errors of omission and commission (Table 3). The five buildings identified as damaged in the ground-based assessment and RPAS visual classification consist of roof edge damages, some of which were from burning building sides identified in the oblique imagery [21]. The four buildings identified as damaged in the RPAS visual classification but not in the ground-based assessment were secondary buildings, some of which might have been metal buildings with contents inside destroyed. Ten buildings were identified as damaged in the ground-based assessment but not identified as damaged in the RPAS visual classification. Six of these buildings had partially burned fences on the property, indicating the presence of first responders.

Table 4
Confusion Matrix Comparing Satellite [11] Visual Classification (VC) for Damage and Destruction to Ground-Based Assessment Results [4] in Coffey Park and Surrounding Urban and Suburban Areas

	Ground-based assessment [4]					
	Destroyed	Damaged	No damage or not assessed	Totals	Commission errors	Producer's accuracy
Satellite VC						
Destroyed	1371	0	505	1876	26.9%	73.1%
Damaged	2	1	7	10	90%	10%
No damage	4	35	1477	1516	2.6%	97.4%
Totals	1377	36	1989	3402		
Omission errors	0.4%	97.2%	25.7%			Overall mapping accuracy = 83.8%
User's accuracy	99.6%	2.8%	74.3%			Kappa statistic = 0.69

Table 5
Kappa Statistics and Overall Mapping Accuracy for the Classifications Assessed Here

Classification	Kappa statistic	Overall mapping accuracy
RPAS visual classification all buildings interface	0.49	76.9%
RPAS visual classification primary buildings interface	0.95	98.6%
Satellite visual classification all buildings interface	0.69	83.8%
Satellite visual classification primary buildings interface	0.96	98.0%
Satellite visual classification same extent as RPAS Interface	0.47	76.5%
Satellite visual classification all buildings intermix	0.57	78.0%
Satellite visual classification primary buildings interface	0.81	90.9%
RPAS Object-based classification Interface	0.73	91.8%
RPAS object-based classification primary buildings interface	0.88	96.4%
Satellite object-based classification interface	0.62	80.4%
Satellite object-based classification same extent as RPAS interface	0.42	72.1%
Satellite object-based classification primary buildings interface	0.88	94.0%
Satellite object-based classification intermix	0.46	78.6%
Satellite object-based classification primary buildings intermix	0.63	85.5%

3.2. *Satellite Visual Classification in Coffey Park and Surrounding Areas*

The satellite visual classification accuracy in Coffey Park and the surrounding urban and suburban areas was 83.8%, with a kappa statistic of 0.69, which Landis and Koch [24] consider a substantial agreement (Table 4). The overall accuracy was 76.5%, with a kappa statistic of 0.47, indicating moderate agreement when considering the same buildings as the RPAS assessment. We portray all the kappa statistics and overall mapping accuracies in Table 5 to compare the various classifications.

The ground-based assessment did not identify 505 buildings identified as destroyed in the visual satellite classification (Table 4). Three of these buildings were small commercial buildings, 492 were secondary buildings, and thirteen were primary buildings, all of which are destroyed in the satellite imagery and missed in the ground-based assessment (Table 1). However, for smaller secondary buildings (e.g., less than 120 ft^2), without a clear foundation in the post-fire imagery, the building might have been moved or removed sometime between the pre-fire imagery (datasets seven, eight, and nine in Table 1) and the fire. Nonetheless, burned areas and ash covered the ground where these destroyed secondary buildings stood in the pre-fire remote sensing data, indicating destruction of features in that area. If the accuracy assessment only considered primary buildings, the overall classification accuracy is 98.0%, and the kappa statistic is 0.96, indicating almost perfect agreement [24].

The satellite visual classification in and around Coffey Park missed 97% of the damaged buildings identified in the ground-based assessment. Also, the satellite visual classification incorrectly classified two destroyed buildings as damaged. Additionally, the satellite visual classification did identify three secondary buildings, three commercial buildings, and one primary building as damaged that the ground-based assessment did not assess. Most of the buildings were partially standing in the satellite imagery, with some portions destroyed. However, the area classified as damaged in one of the buildings was only a shadow, and no damage occurred. Post-fire Google Earth Imagery in 2018 (dataset eight in Table 1) showed the other partially standing buildings as replaced, indicating destruction.

3.3. Satellite Visual Classification in the Intermix Area

The satellite visual classification accuracy in the intermix study area was 78.0%, with a kappa statistic of 0.57, which Landis and Koch [24] indicate as a moderate agreement (Table 6). There were 84 out of 617 buildings (14%) where we could not determine the damage status due to occlusion by vegetation (Table 6). If we only consider primary buildings, the overall accuracy improves to 90.9% and the kappa statistic to 0.81, indicating almost perfect agreement [24].

We classified thirty-nine buildings as destroyed in the satellite visual classification identified as having No Damage or Not Assessed in the ground-based assessment. We classified only one of these buildings as a primary building, and the rest were secondary, or the type of building could not be determined. There were 102 of the 617 (17%) buildings that we could not classify as primary or secondary buildings. In addition, the satellite visual classification did not identify any of the damaged buildings found in the ground-based assessment. Finally, one of the buildings visually classified as damaged was classified as destroyed in the ground-based assessment. Google Earth post-fire imagery from 2018 (dataset eight in Table 1) shows this building as removed, indicating destruction and misclassification in the satellite visual assessment.

3.4. RPAS Object-Based Classification in Coffey Park

The RPAS object-based classification accuracy in Coffey Park was 91.8%, with a kappa statistic of 0.73 (Table 7), indicating substantial agreement [24]. The RPAS object-based classification identified ninety destroyed buildings in the RPAS visual assessment and ground-based assessment as surviving. Sixty-eight of these buildings were small secondary buildings, and twenty-two were primary buildings. The RPAS object-based classification incorrectly identified 78 surviving buildings as destroyed. Twenty-five of these buildings were primary buildings, and fifty-three were secondary buildings. The kappa statistic is 0.88, indicating almost perfect agreement [24], and the overall classification accuracy is 96.4% when only considering primary buildings.

3.5. Satellite Object-Based Classification in Coffey Park Area and Intermix

The satellite object-based classification accuracy in and around Coffey Park was 80.4%, with a kappa statistic of 0.62 (Table 8), indicating a substantial agreement [24]. The satellite object-based classification incorrectly identified 20 destroyed primary buildings as surviving. The satellite object-based classification identified 646 surviving buildings as destroyed. One-hundred and thirty-three of these buildings

Table 6
Confusion Matrix Comparing Satellite [11] Visual Classification (VC) for Damage and Destruction To Ground-Based Assessment Results [4] in the Intermix Study Site. Note that we Include ''Not Determined'' Buildings From The Satellite Classification, and There Are no ''NOT Determined'' Categories in The Ground-Based Assessment. Not Determined is Different than ''Not Assessed'' as it Implies an Attempt to Assess the Building Unsuccessfully

Ground-based assessment [4]							
	Destroyed	Damaged	No damage or not assessed	Not determined	Total	Commission errors	Producer's accuracy
Satellite VC							
Destroyed	134	2	39	0	175	23.2%	76.6%
Damaged	1	0	0	0	1	100%	0
No damage	0	10	347	0	357	2.8%	97.2%
Not determined	20	3	61	0	84	Not applicable	Not applicable
Totals	155	15	447	0	617		
Omission errors	13.5%	100%	22.4%	No data			Overall mapping accuracy = 78.0%
User's accuracy	86.5%	0%	77.6%	No data			Kappa statistic = 0.57

Table 7
Confusion Matrix Comparing RPAS [10] Object-Based Classification (OBC) for Destruction to Combined Results from Ground-Based Assessments [4] and the RPAS Visual Classification (VC) in Coffey Park

Combined ground-based assessment [4] and VC					
	Destroyed	Surviving	Totals	Commission errors	User's accuracy
RPAS OBC					
Destroyed	1567	78	1645	4.7%	95.3%
Surviving	90	307	397	22.7%	77.3%
Totals	1657	385	2042		
Omission errors	5.4%	20.3%			Overall mapping accuracy = 91.8%
Producer's accuracy	94.6%	79.7%			Kappa statistic = 0.73

Table 8
Confusion Matrix Comparing Satellite [11] Object-Based Classification (OBC) for Destruction to Combined Results from Ground-Based Assessment [4] and the RPAS Visual Classification (VC) in Coffey Park

Combined ground-based assessment [4] and VC					
	Destroyed	Surviving	Totals	Commission errors	User's accuracy
Satellite OBC					
Destroyed	1233	20	1253	1.6%	98.4
Surviving	646	1503	2149	30.1%	69.9%
Totals	1879	1523	3402		
Omission errors	34.4%	1.3%			Overall mapping accuracy = 80.4%
Producer's accuracy	65.6%	98.7%			Kappa statistic = 0.62

were primary buildings, and five hundred and thirteen were secondary buildings. When considering only the buildings within the extent of the RPAS imagery, the kappa statistic is 0.42, indicating moderate agreement [24], and the overall mapping accuracy is 72.1%. The kappa statistic is 0.88, indicating almost perfect agreement [24], and the overall classification accuracy is 94.0% when considering only primary buildings.

The satellite object-based classification accuracy in the intermix study area was 78.6%, with a kappa statistic of 0.46 (Table 9), indicating a moderate agreement

Table 9
Confusion Matrix Comparing Satellite [11] Object-Based Classification (OBC) for Destruction to Combined Results From Ground-Based Assessment [4] and the Rpas Visual Classification (VC) in the Intermix Study Area

Combined ground-based assessment [4] and VC					
	Destroyed	Surviving	Totals	Commission errors	User's accuracy
Satellite OBC					
Destroyed	99	34	133	25.6%	74.4%
Surviving	98	386	484	20.2%	79.8%
Totals	197	420	617		
Omission errors	49.7%	8.1%			Overall mapping accuracy = 78.6%
Producer's accuracy	50.3%	91.9%			Kappa statistic = 0.46

[24]. The satellite object-based classification identified 98 surviving buildings as destroyed compared to combined satellite visual classification and ground-based assessment results. Thirty-seven of these buildings were not determined, thirty-nine were secondary buildings, and twenty-two were primary buildings.

Also, the object-based satellite classification identified 34 surviving buildings as destroyed. Nine of these buildings were not determined, fifteen were secondary buildings, and ten were primary buildings. If the accuracy assessment only considered primary buildings, the kappa statistic is 0.63, indicating substantial agreement [24], and the overall classification accuracy is 85.5%. Implementing machine learning functionality in Feature Analyst™ did not improve classification results in the intermix study site.

3.6. Defensive Action Identification and Effectiveness in Interface Area

In Fig. 3, we show a map of defensive actions surrounding homes in the interface study area. We confirmed ten locations (covering multiple properties though we could not always determine the full extent of defensive actions in the images and videos) in Coffey Park as defended through videos, images, and eyewitness accounts found on the internet. There is a correlation between images, videos, and eyewitness accounts of first responders and a homeowner actively suppressing burning buildings with water and a building's darkened appearance, partially standing walls, partially burned features, or partially standing buildings compared to neighboring lighter and entirely destroyed buildings. The unhindered complete combustion of building materials results in white ash accumulation and a lighter appearance with less partially burned features. The darker appearance is due to the cessation of the combustion process through water suppression.

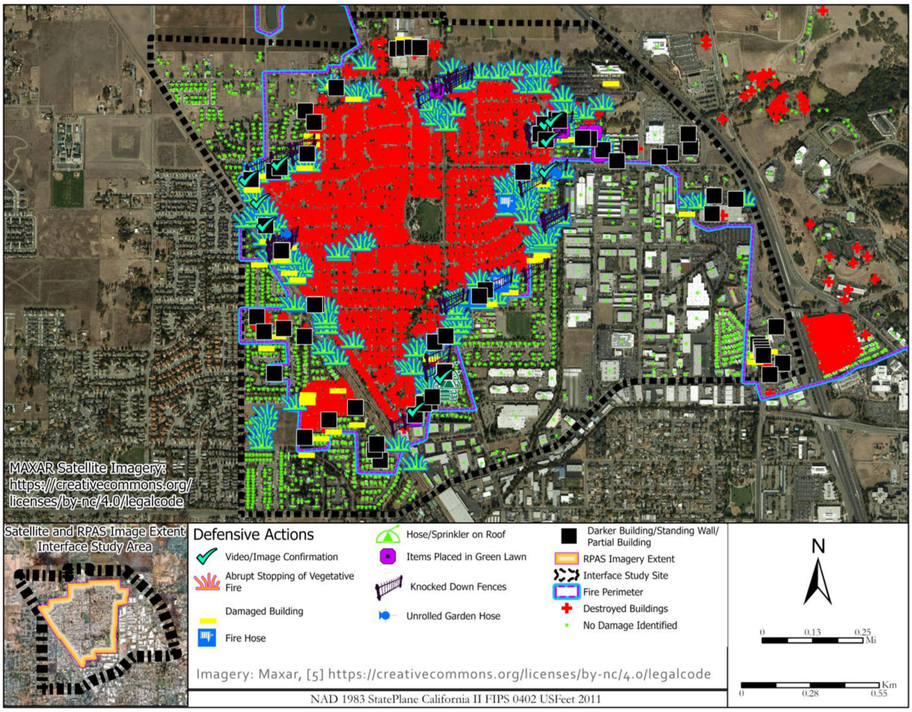


Figure 3. Defensive actions in and around Coffey Park.

In one location, photographers [39] filmed first responder actions that resulted in a standing wall on the home's defended side. This standing wall is also visible in the RPAS imagery (Fig. 2). The building side not defended did not have a standing wall. First responders defended this building during high wind conditions on the fire's flanking (eastern) side in Coffey Park [39]. Other defensive actions also occurred on the fire's flanking side during high wind conditions [39]. These actions were successful at stopping fire spread in these locations to buildings and elsewhere.

In one case, KPIX 5 CBS [25] and SFGATE [44] documented a homeowner as actively spraying water between his home and the neighbors using a fire hose obtained from first responders. This location resulted in a standing wall on the surviving building side, which received water suppression and destruction of all other walls, not receiving water suppression. By the time the fire reached this property, the wind conditions had abated and changed directions. We found no other ground-based videos, images, or accounts of homeowners defending in and around Coffey Park. However, this does not indicate that no other homeowners or business owners defended in and around Coffey Park.

The majority of areas showing an abrupt stop of fire spread in vegetation occurred where building destruction also ceased. These locations were typically spatially coincident with signs of defensive actions (e.g., knocked down fences).

However, the abrupt cessation of fire spread in vegetation on the northwestern end of Coffey Park was not coincident with the end of building fire spread or other defensive actions. These locations might have been where building fires in Coffey Park were initiated and could represent initial and failed defensive actions or locations where there was changing fire behavior.

The abrupt cessation of vegetative fires was not always apparent in the coarser spatial resolution satellite imagery compared to the RPAS imagery. Signs of defensive actions such as sprinklers on roofs, unrolled garden/fire hoses, knocked down fences, and partially burned fences were only visible in the RPAS imagery. Buildings with a darker appearance were evident in both the satellite and RPAS imagery. However, the RPAS imagery provided more details regarding partially burned features.

The chi-square results to test hypothesis 1 showed a Pearson value of 935.2 (p-value < 0.00001). This result was consistent with the conclusion that surviving buildings bordering destroyed and damaged buildings in and around Coffey Park depended, in part, on defensive actions occurring on nearby destroyed or damaged buildings or properties. Building owners might also need to implement previously identified building and landscape treatments e.g., [26, 27, 28 and 29] or other unknown treatments to facilitate successful defense by first responders.

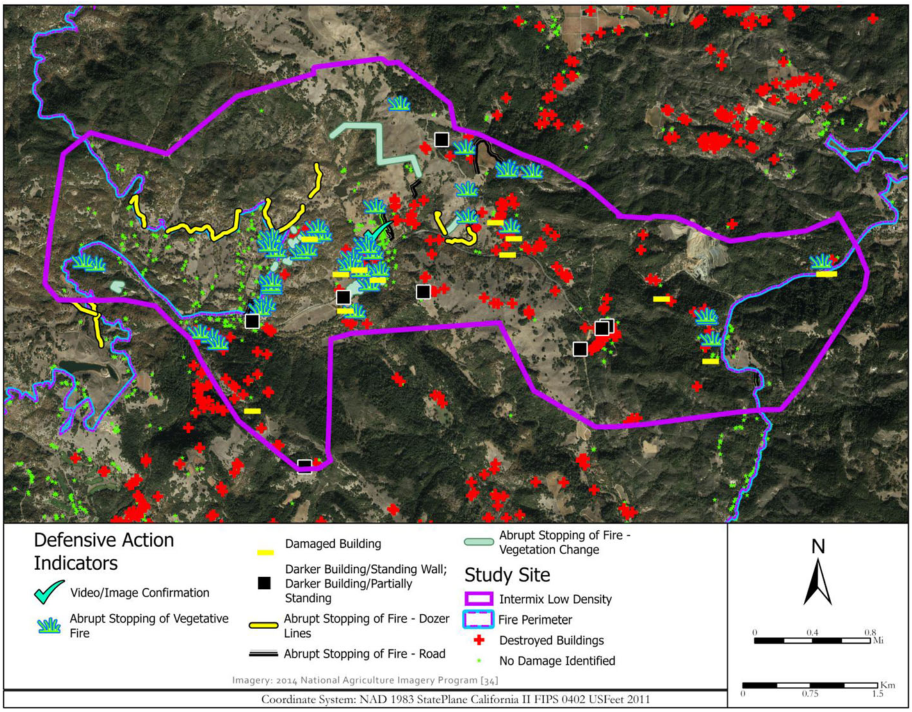


Figure 4. Defensive actions in and around the intermix study area.

3.7. Defensive Action Identification and Effectiveness in the Intermix Area

Figure 4 shows a map of defensive actions identified from the satellite imagery (Table 1) and one eyewitness account [30] in the intermix study area. We did not identify any knocked-down fences, hoses, or items placed on a green lawn from the satellite imagery. We confirmed only one location as defended through videos and images found on the internet [30]. However, this area encompassed many buildings.

We did not find any images or videos of first responders actively suppressing buildings with water in the intermix area. However, four buildings with a darker appearance were partially standing. In addition, three destroyed buildings had a darker appearance than neighboring destroyed buildings. One building also had a standing wall on only one side of the destruction, which we identified as an indicator of defensive actions through videos in Coffey Park [39] and eyewitness accounts [25].

We show that many surviving buildings are adjacent to or surrounded by defensive action indicators (Fig. 4). Also, many areas with large clusters of destroyed buildings have limited or no indicators of defensive actions. For example, defensive actions surround the larger cluster of continuous surviving buildings partially

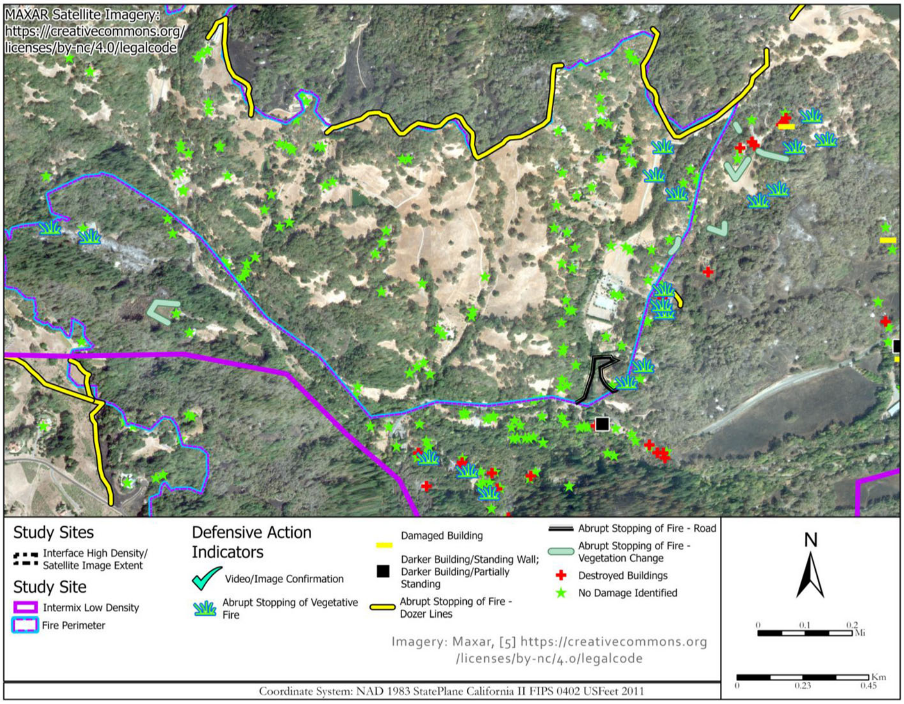


Figure 5. Defensive actions on the western side of the fire perimeter in the interface study area. Defensive actions surround buildings with no damage.

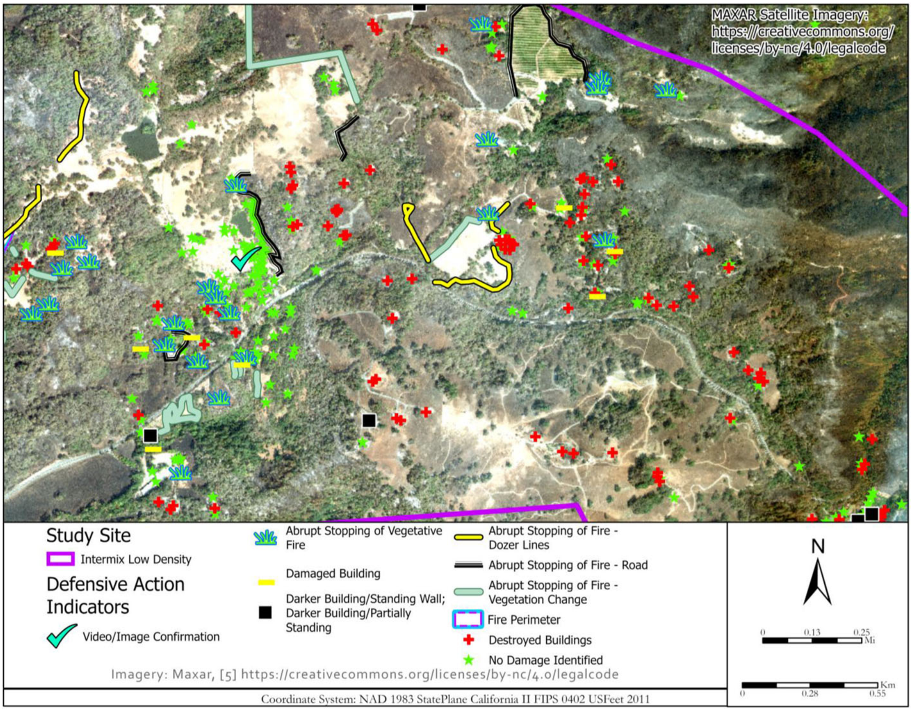


Figure 6. Defensive actions in the center of the intermix area. Defensive actions do not surround clusters of destroyed buildings. The larger cluster of buildings with no damage is mostly in the Safari West animal park, which the owner defended [30].

outside the fire perimeter's western side (Fig. 5). Furthermore, indicators of defensive actions also surround the larger cluster of surviving buildings in the center of the study area (Fig. 6). There is documentation of the property owner in this area (Safari West) staying and defending the property [30].

Some of the indicators of defensive actions such as abrupt stopping of fire spread at roads and changes in vegetation conditions might not have been from active fire defensive actions. Instead, varying heat fluxes (i.e., exposure conditions) coupled with pre-fire human intervention (e.g., roads or altered vegetation) might have resulted in fire behavior changes in these areas. However, in some locations, the abrupt stopping of fire spread was associated with other indicators of defensive actions such as fire or garden hoses adjacent to the abrupt stopping of fire (e.g., Fig. 2). Regardless, the outcome is similar to defensive actions because the resulting reduction of exposure (i.e., heat fluxes) might contribute to building survival.

4. Discussion

Like McNamara et al. [8], we found that visual classification for destroyed buildings using satellite and RPAS post-fire imagery had similar results to the ground-based assessment for primary buildings. However, the RPAS and satellite visual classification in the interface study area was more accurate than the ground-based assessment for identifying secondary building destruction. In part, the higher accuracy from the RPAS and satellite imagery might be due to the ground-based assessment focusing on buildings with footprints larger than 120 ft^2 (11.1 m^2) as per California building codes requiring buildings greater than 120 ft^2 (11.1 m^2) to be Sect. 7a compliant.

The visual classification also identified some destroyed primary buildings missed by the ground-based assessment. It is unknown why the ground-based assessment missed these buildings, and they might be data entry errors. Nonetheless, when considering the same extent as the RPAS imagery in Coffey Park, the satellite visual classification had a similar kappa statistic and overall mapping accuracy as the RPAS visual classification for destroyed buildings (Table 5).

We could not determine exact building areas from the datasets used here (i.e., datasets two, three, four, and five) to identify building footprints smaller or greater than 120 ft^2 (11.1 m^2). Nonetheless, examining the distributions of the planar building area (Fig. 8) highlights that the use of remote sensing data (datasets three, four, and five in Table 1) identified secondary buildings not identified in the ground-based assessment. For example, only three destroyed buildings were assessed [4] in the two study areas with a planar area less than 120 ft^2 (as measured from the cartographic building footprints: dataset two in Table 1).

In comparison, the RPAS visual assessment identified 432 destroyed buildings with a planar area less than 120 ft^2 (Fig. 8). These discrepancies could be because damage inspectors did not focus on smaller buildings (i.e., less than 120 ft^2), could not identify smaller secondary buildings in the field, or both. Additionally, we could not perform a ground-based assessment before the fire to verify the presence of the smaller secondary buildings (e.g., less than 120 ft^2).

Regardless, the missed secondary buildings point to a possible underestimation of secondary buildings' role in destroying primary buildings, but further study is required to confirm this hypothesis. In addition, one of the few studies attempting to account for the role of secondary buildings when assessing building response to WUI fires found that detached secondary buildings can cause significant risk to primary buildings [31]. Finally, identifying partially burned fences and knocked down fences provides evidence of the hazard due to combustible fences and the need for first responders to extinguish fences once ignited.

These results highlight that the ground-based assessment did miss some destroyed secondary buildings due to logistical difficulties in field identification. For example, logistical difficulties could include identifying a small building with no foundation from a pile of ash, time constraints due to the emphasis on assessing primary building damage and destruction, not examining the entire property due to size, safety, and other constraints. Given these logistical difficulties with ground-based assessments, we show remote sensing can be a promising addition to ground-based assessments to efficiently and effectively identify destroyed buildings.

Visual classification of satellite and RPAS imagery was rapid in both study areas requiring only one operator (less than three hours). Satellite imagery can be collected relatively quickly after the incident. However, satellite imagery can suffer from occlusion from smoke and clouds, which was the case for some post-fire satellite imagery shown in Google Earth (Table 1).

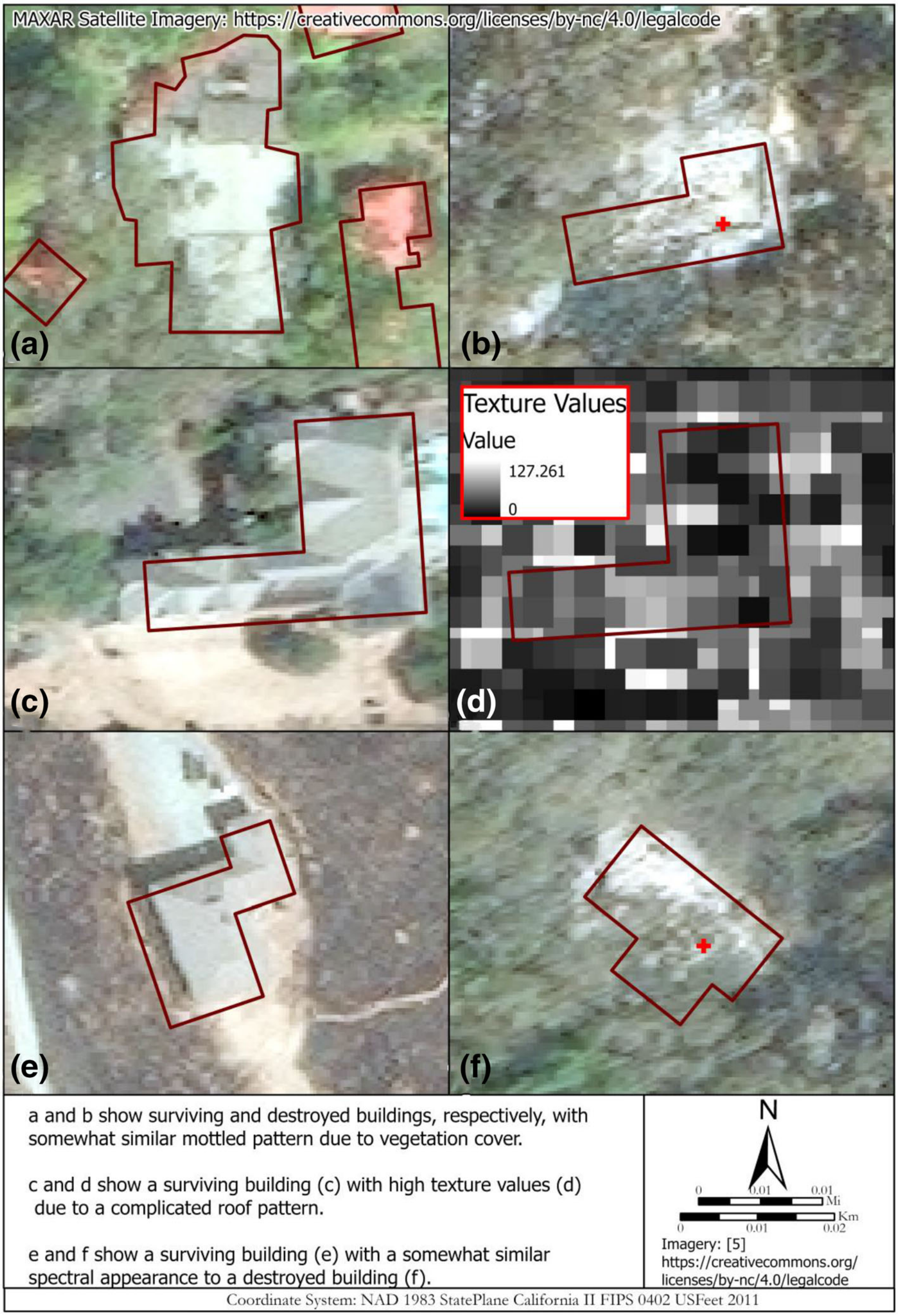
Acquiring RPAS imagery can, at times, occur below the smoke and cloud cover. Also, certified specialists can mobilize quickly for RPAS imagery. However, such teams' mobilization might not be efficient everywhere. Satellite imagery is available globally e.g., [11]. Other areas with destruction had RPAS image acquisitions demonstrating the utility of this type of imagery for the safe assessment of high-density building areas. However, acquiring RPAS imagery over large areas is challenging, given current regulations in some countries.

Visually classifying RPAS imagery missed damage identified from ground-based observations. This damage appeared to be on the side of a building or in the interior. Visually classifying satellite imagery missed almost all the damage due to its relatively coarse spatial resolution. Nonetheless, damage inspectors can use the correlation between destroyed buildings, partially burned fences, damaged buildings, partially burned vegetation, and adjacent destroyed buildings to focus on collecting RPAS oblique imagery in these areas. This focus can reduce potential exposure to toxic debris by ground-based damage inspectors.

Unlike McNamara et al. [8], remote sensing did not identify any roof damage missed in the ground-based assessment. Presumably, all the roof damage was due to exposure from the building's sides' burning. In addition, there did not appear to be wood roofs in the interface area, whereas the study site examined by McNamara et al. [8] had numerous wood roofs.

The object-based classification of primary buildings using RPAS and satellite imagery had similar overall results (Table 5), particularly when considering only primary buildings. However, the object-based satellite classification had more difficulty identifying small destroyed secondary buildings due to the coarser spatial resolution resulting in more high texture values along roof edges that encompassed the entire small building footprint. Additionally, object-based classifications produced more commission and omission errors than those found in McNamara et al. [8]. In part, the more significant number of commission and omission errors was due to taller trees and more vegetation cover occluding building areas in both study sites compared to the study site assessed by McNamara et al. [8].

The satellite imagery collected data at an off-nadir look angle, resulting in leaning tall features such as trees and standing buildings. This leaning can result in long shadows or occlusion from vegetative cover within building areas. The object-based classification did not classify these occluded or shadowed areas as destroyed, resulting in higher omission errors for destroyed buildings in both the intermix and interface study area using the satellite imagery than the RPAS imagery. In addition, more leaning trees and higher canopy cover contributed to


MAXAR Satellite Imagery: https://creativecommons.org/licenses/by-nc/4.0/legalcode
(a)
(b)
(c)
Texture Values
Value
127.261
0
(d)
(e)
(f)
a and b show surviving and destroyed buildings, respectively, with somewhat similar mottled pattern due to vegetation cover.
c and d show a surviving building (c) with high texture values (d) due to a complicated roof pattern.
e and f show a surviving building (e) with a somewhat similar spectral appearance to a destroyed building (f).
N
0
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https://creativecommons.org/licenses/by-nc/4.0/legalcode
Coordinate System: NAD 1983 StatePlane California II FIPS 0402 USFeet 2011

◂**Figure 7. Surviving (a, c, d, and e) and destroyed (b and f) buildings with similar characteristics producing classification errors. High texture values typically do not cover surviving buildings unless there is a complicated roof geometry (e.g., c and d) or canopy cover (e.g., b and f).**

lower classification results for satellite imagery in the intermix area than the interface area.

There also appeared to be more significant spectral variability within the destroyed building footprints in the satellite imagery than the RPAS imagery, resulting in lower classification accuracy for satellite imagery and the need for more training sites. Atmospheric reflectance could, in part, account for this variability. Therefore, corrections for atmospheric reflectance might normalize the satellite imagery and improve classification results.

The time of year of image acquisition contributed to the higher errors regarding committing destroyed buildings to the surviving building category using the object-based classification compared to McNamara et al. [8]. The imagery used in the McNamara et al. [8] study was acquired in June when the sun was more directly overhead. The lower solar angle for the Tubbs Fire imagery produced wider variation in some buildings roofs' spectral reflectance. This variation (high texture values) resulted in more classified destroyed areas being committed to surviving buildings in the RPAS and satellite classifications than the imagery used by McNamara et al. [8].

Also, the buildings in this study area had more solar panels on the roofs than the McNamara et al. [8] study area. These solar panels resulted in high texture values and classification of some surviving buildings as destroyed. Finally, a more significant misalignment of building footprints to the satellite and RPAS imagery reduced classification accuracies, in some cases, compared to the McNamara et al. [8] study, which had better alignment between footprints and post-fire imagery.

The Feature Analyst™ machine learning did not correct commission errors resulting from high texture values produced by roof tile or shingle shadows. Also, the machine learning implemented here will not account for significant spatial misalignment between building footprints and imagery or surviving buildings with high texture values due to complicated roof configurations, small building footprints, or significant obtrusions (e.g., solar panels). Finally, the machine learning implemented here does not account for misclassification caused by canopy occlusions. Post-fire LiDAR data, which might penetrate the canopy better than passive remote sensing techniques examined here, could improve classification results, but further study is required.

Spectral and textural similarities between destroyed and surviving buildings (Fig. 7 a and b, and e and f) contributed to classification errors in the intermix study site. Buildings with complicated roof patterns produced high texture values exaggerated by the coarser spatial resolution (Fig. 7 c and d). Mottled patterns in buildings covered by vegetation resulted in surviving buildings that were spectrally similar to destroyed buildings in some cases (Fig. 7 a and b). Finer spatial resolu-

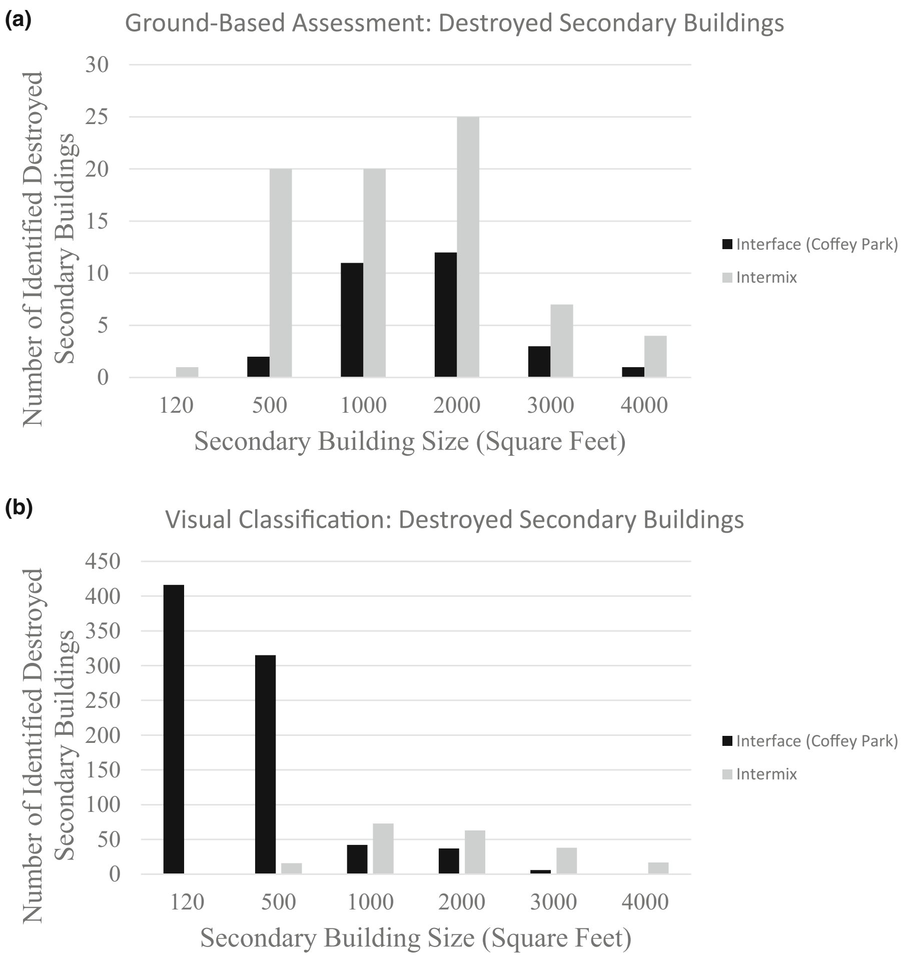

Figure 8. Histograms portraying destroyed secondary building area identified from a Ground-based assessments [4] and b Visual image assessments of the remote sensing data for both study sites.

tion data might improve results in intermix areas with such features. Future studies should also examine the use of additional machine learning algorithms e.g., [32].

Crowdsourcing of active fire data provides valuable information about WUI fires. However, given the large number of individuals present at the fire (e.g., first responders and evacuees), there may be a far greater number of images, videos, and first-hand accounts of defensive actions and fire behavior recorded than we found on the internet. In addition, the traumatic nature of the event for evacuees and first responders, coupled with concerns of liability, might reduce the availability of active fire images, videos, and first-hand accounts. (Fig. 8).

The images and videos used here also lacked temporal information in some cases. Geolocating active fire images is a time-consuming process. We examined significantly more images and videos than listed in Table 2 as many of these did not portray information for our study sites. We found geolocation more difficult in the intermix area partially due to buildings being further from the road and more difficult to correlate with pre-fire Google Street View imagery (Table 1).

Similar to McNamara et al. [8], we found a significant dependence between stopping fire spread and defensive actions at the interface study area. It is more difficult to statistically test the effects of defensive actions in the intermix study area due to the more significant variation in building spacing. Nonetheless, defensive actions, some possibly pre-fire (e.g., abrupt changes in vegetation conditions), are correlated with clusters of surviving buildings. Other factors likely contributed to the ability of first responders to stop fire spread. For example, some first responders [33] stated that diminished and changing wind conditions aided their efforts (i.e., winds moved from the northeast to the southwest, toward the direction of previously destroyed buildings in the Coffey Park area).

Additionally, we presume that based on the number of apparatus seen entering Coffey Park [33], the assessment of defensive actions presented here underestimates defensive actions' full extent. We could not identify from overhead imagery defensive actions occurring under canopied areas or the interior of buildings. Also, defensive actions identified by remote sensing do not account for the total quantity and type of defensive actions, nor does remote sensing identify failed defensive actions readily [8].

Regardless, the use of remote sensing to rapidly identify defensive actions highlights the importance of accounting for defensive actions when assessing building response in both interface and intermix areas at the Tubbs Fire. As with the 2012 Waldo Canyon Fire [8], a thorough building response assessment would consider buildings initially ignited in the study sites and buildings not ignited during the passage of the wildland fire front that received similar heat fluxes. Identification of this population of buildings is challenging in any post-fire environment.

It is common in post-fire assessments of building response to assess all buildings within the fire perimeter. However, this sample selection can be arbitrary, as shown when examining Figs. 5 and 6. Buildings outside the fire perimeter (Fig. 5) may have survived due to defensive actions, which are often not considered in assessing building response. Additionally, some buildings inside the fire perimeter (Fig. 6) survived, in part, because of defensive actions. In effect, they are outside the fire perimeter in terms of assessing building response.

Furthermore, the consequences of active fire (Fig. 5) and pre-fire (Fig. 6) defensive actions relatively far from surviving buildings might have consequences for building survival. Conditions far from buildings are typically not considered in the assessment of building response. Further study is needed to understand defensive actions and WUI treatments nearby and relatively far from buildings to understand where and under what conditions to focus pre-fire and active fire efforts.

While this study does add to the growing body of evidence supporting the need to consider defensive actions when assessing building response to WUI fires e.g., [12, 13, 14, 15 and 16], further study is required to understand the complex interaction between environmental factors (e.g., building materials, code compliance, vegetation properties, and others), WUI fire behavior, defensive actions, and building response. The techniques presented here can aid in understanding the location of defensive actions. Nonetheless, identifying specific information on defensive actions (e.g., failed actions and equipment type) requires automated vehicle logs, images and videos with time stamps, and information from fire witnesses e.g., [1 and 7].

Finally, identifying specific damaged features rather than the percent of building damage provides a means to identify building vulnerabilities. Also, rather than proving that current WUI treatments are effective, which is almost impossible, identifying failures of current WUI treatments in specific locations could help improve WUI mitigation advice. The improved efficiency resulting from remote sensing for building destruction might facilitate this detailed assessment of the building vulnerabilities and mitigation failures.

5. Conclusions

This study provides additional evidence of remote sensing's usefulness to assess building damage, destruction, and defensive actions. Synergistic use of ground-based and remote sensing assessments is required to fully assess damaged features and features occluded by canopy cover, tall buildings, clouds, and shadows. Automated and semi-automated techniques also show promise for the rapid identification of destroyed buildings.

Satellite, fixed-wing e.g., [8], and RPAS image acquisitions all have advantages and disadvantages. The acquisition of open imagery from satellite sources e.g., [11] is becoming commonplace at large WUI fires. It promises to provide a consistent source for the assessment of building destruction from WUI fires. RPAS imagery provides more detail on damage and defensive actions but might be more challenging to acquire for large areas and some locales. Fixed-wing acquisitions might be challenging to acquire due to mobilization requirements but can provide high-spatial-resolution data, similar to RPAS, over a large area. Regardless, synergistic use of various types of image sources, as available, can increase the efficiency and safety of ground-based damage assessments at WUI fires.

Despite the usefulness of active fire images, videos, and personal accounts on the internet, there is a need for discussions e.g., [1] or coordinated electronic crowdsourcing of fire witness observations. Nonetheless, the coordinated acquisition of videos and images of active fire conditions and actions should be an initial step to reconstructing the fire timeline and defensive actions. This crowdsourcing can, in part, occur through electronic applications [34], thereby more efficiently guiding discussions. Also, both first-responders and other fire witnesses should be encouraged to openly share active fire images, videos, and accounts using standard protocols to help future communities affected by WUI fires.

It is challenging to identify the surviving population of buildings that received heat fluxes (i.e., exposures from flames and embers) similar to buildings destroyed by WUI fires, confounding building response assessment. Identifying surviving buildings based on their inclusion within the fire perimeter or adjacency to destroyed buildings might be an arbitrary sampling approach. Consequently, identifying damaged building components and WUI mitigation failures is useful. Furthermore, studies attempting to assess building response should include comparisons to outcomes at nearby WUI treatments and some distance from affected buildings.

In conclusion, this study builds on the growing body of evidence supporting the synergistic use of post-fire imagery (e.g., building destruction) and ground-based assessments (e.g., building damage) to provide efficient and safe approaches to identifying damaged, destroyed, and defended buildings. Crowdsourced information from active fire images and videos is also a valuable source of information for post-fire assessments. The more ubiquitous use and availability of these data sources promise to increase our understanding of WUI fires and factors leading to building destruction and survival.

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Data Availability

Data used to support this paper is publicly available via the references included in the paper.

Declarations

Conflicts of interest The authors declare no conflict of interest.

Consent for Publication We provide consent for publication.

SUPPLEMENTARY INFORMATION

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