

Article

UAV-Based Estimation of Fuel Structure and Dynamics in a California Canyon Fire Experiment

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Highlights

What are the main findings?

- UAV-based multispectral, infrared, and visible imagery documented fuel and vegetation conditions before, during, and after a prescribed upslope canyon fire.
- UAV photogrammetry and supervised object-based classification produced high-resolution fuel maps and fuel-height change estimates that corresponded with ground-based fire-severity indicators and fuel type.

What are the implications of the main findings?

- The proposed UAV workflow provides a repeatable protocol and baseline dataset for long-term monitoring of fuel-height loss and post-fire vegetation regrowth.
- Integrating UAV remote sensing with ecological field sampling can improve fine-scale assessment of post-fire vegetation structural change and support prescribed-fire monitoring.

Abstract

Wildfires in California increasingly threaten communities and ecosystems. However, comprehensive estimation of fire dynamics and fuel structure remains limited. Recent advances in Uncrewed Aerial Vehicle (UAV) technology and high-spatial-resolution mapping have provided increasingly important tools for estimating wildfire fuel-height loss across fuel types. This study used a one-year Uncrewed Aerial Vehicle (UAV) time series to quantify fuel-height loss and vegetation regrowth associated with a prescribed upslope canyon fire near Salinas, California, USA. Multispectral, infrared, and visible UAV imagery collected before, during, and after burning was used to generate orthomosaic, digital surface models (DSMs), fuel-type classifications, and surface-volume estimates. To enable reliable pre- and post-fire comparison, ground control points and tie points were used to train linear regression calibrations that corrected angular discrepancies and elevation offsets among



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time-series DSMs. Calibrated DSMs were then integrated with ecological field measurements to map fuel-height consumption and post-fire recovery at the individual-plant scale. UAV-derived fuel-height change was associated with in situ twig-diameter measurements, which provide field-based indicators of fire effects in chaparral vegetation, while the maximum recorded temperature explained only a small proportion of variation in fuel-height loss. This workflow can support integrated fire ecology and remote-sensing studies by providing repeatable measurements of post-fire changes in vegetation structure.

Keywords: uncrewed aerial vehicles; UAV photogrammetry; multispectral remote sensing; fuel-height change; prescribed fire; object-based classification

1. Introduction

The increasing frequency and severity of wildfires in recent years in California and the United States have heightened safety concerns and increased research attention at local, regional, and global scales [1–3]. According to the US National Interagency Fire Center (NIFC), the United States experienced 64,897 fires in 2024. Although this was the seventh-lowest annual number recorded over the past 25 years, these fires still burned 8,924,884 acres [4], and California remains particularly affected by wildfire activity. The California Department of Forestry and Fire Protection (CAL FIRE) reported 8110 wildfires that consumed 1,077,711 acres in the same year [5,6]. Wildfires can devastate natural habitats, impact biodiversity, degrade air quality, accelerate climate change, and cause long-term damage to ecosystems and human health [7–9]. These multifaceted threats necessitate a comprehensive understanding and coordinated action, underscoring the urgent need for in-depth research into the ignition, development, spread, and consequences of wildfires [10,11]. Such research is crucial for understanding fire trends, their drivers, and their impacts and for developing effective monitoring and intervention strategies.

Accurate estimates of fuel load, fuel consumption during wildfire, and associated spatial variability are important for wildfire mitigation, fire ecology, vegetation restoration, emissions estimation, atmospheric chemistry, and climate-change studies [12]. Research indicates that detailed fuel-load data collected over time, capturing pre- and post-fire conditions, provide greater insight into burned areas, emissions, and fire severity than infrequent average measurements [12,13]. This highlights the importance of methods that are easy to deploy and consistently reliable. Standard methods for biomass estimation by fire enforcement departments often rely on comparing in situ vegetation with reference images from handbooks, a process dependent on practitioner experience, but effective for rapid assessment to support wildfire operations [14]. While in situ measurements offer high fidelity and accuracy without reliance on modeling assumptions, they are often labor-intensive and time-consuming, particularly in large-scale studies. Extrapolating sampled data to represent an entire study area introduces spatial limitations and potential bias. Furthermore, access to post-fire landscapes can be hazardous, posing safety risks to field personnel. In addition to the direct estimation methods, some studies focus on predicting fuel load using biophysical or statistical models incorporating multiple variables, such as elevation, total annual precipitation, and average annual temperature [13,15]. Satellite imagery is commonly used to derive multispectral vegetation indices and fire-severity metrics, such as delta normalized burn ratio (dNBR), relative delta normalized burn ratio (RdNBR), and the relative burn ratio [16,17]. While these methods are efficient for large-scale fuel-load estimation, they lack the high resolution needed for precise fire management and cannot provide specific results for localized wildfires [18,19].

Recent advancements in Uncrewed Aerial Vehicle (UAV) technology, particularly in sensor development, automated flight controls, and battery life, have made drones increasingly important in wildfire research and management [20–22]. UAVs offer ultra-high-resolution, centimeter-scale imaging and the flexibility for rapid deployment before or during anticipated fire events, whereas satellite imagery is often limited by coarser spatial resolution and longer revisit intervals [23]. This capability is especially beneficial for monitoring rapidly changing and intense events like wildfires and for conducting repeated, multi-temporal imagery data collection. UAVs can be equipped with multispectral sensors and airborne Light Detection and Ranging (LiDAR) systems as highly effective airborne platforms. This integration can be used to produce multiple geospatial data products, including RGB maps, Normalized Difference Vegetation Index (NDVI) imagery, 3D characterization, and DSMs for observing and analyzing wildfires, aiding in fire prevention, control, and post-burn assessment [24–27]. Spectral band indices, such as Excess Green Index and Modified Excess Green Index from UAV data, have been used to represent fire severity [28]. Although LiDAR and UAV imagery provide comparable vegetation height measurements [29,30], LiDAR lacks multispectral capabilities and has more limited spatial coverage than UAV optical systems. Its effectiveness is further constrained by overstory obstruction and noise, as dense canopy cover reduces its accuracy in mapping understory vegetation and surface fuels [27].

To estimate high-resolution fuel dynamics, data needs to be rigorously georeferenced and calibrated. Several key factors can contribute to the tilting problem in UAV-based DSMs, such as camera calibration, orientation, image overlap and coverage, and the sun's height and angle [31,32]. Among all of these factors, sun elevation and solar angle are some of the dominant and difficult-to-avoid factors. The sun's height and angle affect the shadows and illumination in the UAV images. Lower sun angles create longer shadows than higher angles, distorting the surface features. Shadows can obscure vegetation color and structure, unlike shadows cast by built structures, which often show a clear boundary and are less likely to be affected by shadows. Consequently, shadows affect the accuracy of the DSMs. Sometimes, changes in sun angles can cause variations in surface reflection, leading to inconsistencies in the UAV images. In addition to these factors, post-fire DSMs created using UAV images often show distortion and tilting, especially in large areas covered by ash or charred vegetation. The tilting hinders optimal elevation reconstruction and introduces errors in pre- and post-fire fuel elevation comparison, which reduces the effectiveness of UAV photogrammetry as a high-resolution data-collection method. Some proposed solutions include building a quality digital terrain model (DTM) or applying real-time kinematic (RTK) positioning to optimize the data collection [32].

Prescribed fires are an established tool for wildfire risk mitigation through vegetation management. These controlled burns are systematically planned by governmental agencies and landowners, with site selection based on fire intensity, safety protocols, and potential impacts on surrounding communities [33]. This pre-planning provides an optimal framework for scientific research, enabling researchers to deploy equipment in advance to collect comprehensive data during the burn and analyze fire behavior and dynamics effectively. In this study, CAL FIRE conducted a large-scale fire experiment in a canyon near Salinas, Northern California, providing a unique opportunity to collect data on fire behavior in one of the most hazardous wildfire terrains [34–36]. Our research team led the data-collection experiment, working closely with CAL FIRE to plan and coordinate the acquisition of pre- and post-fire datasets.

Building on these previous approaches, this study emphasizes repeat UAV-based DSM differencing to quantify pre- and post-fire vegetation structural change. Unlike approaches based primarily on spectral burn indices, LiDAR-derived fuel structure, or field

sampling alone, this study integrates repeated UAV imagery, calibrated SfM-derived DSM differencing, object-based fuel-type classification, and field twig-diameter measurements to estimate fuel-height loss and post-fire recovery. The primary objectives of this study were to develop and implement a comprehensive approach for estimating fuel-height loss using UAV RGB images captured before and after the fire experiment. By correcting georeferencing errors and tilt in multi-temporal DSMs, we aimed to estimate pre- to post-fire changes in vegetation height. This methodology supports plant-level analysis of fuel-height loss and vegetation recovery at an unprecedented individual-plant scale (i.e., each shrub or tree crown treated as a separate object), contributing to the ecological management of critical chaparral habitats in California. The calibrated DSMs from this controlled canyon burn also provide a basis for cross-disciplinary analyses integrating fire behavior, fire ecology, meteorology, and environmental science. These DSMs were accurately adjusted using standardized, reproducible geospatial technologies, incorporating ground control points and ecological field studies. We analyzed the relationship between fuel-height loss, fuel types, and temperature during the fire. A standardized protocol was developed for DSM tilting calibration and fuel estimation, enabling the derivation of fuel-height change due to the fire and facilitating the analysis of vegetation regrowth using subsequent repeated sampling over a long time series at an individual-plant scale using UAV imagery.

This study contributes a validated UAV-DSM workflow for quantifying fine-scale fuel-height loss and early post-fire vegetation recovery after prescribed fire, with emphasis on DSM calibration, independent validation, fuel-type classification, and comparison with field-based fire-effect indicators.

2. Study Site

The study area is a designated prescribed-fire zone located on a private ranch near Salinas, California (Figure 1). On 24 October 2022, CAL FIRE conducted a prescribed, upslope canyon fire on a west-facing slope within the Gabilan Mountain Range. Canyon topography is among the most hazardous wildfire terrains because it promotes eruptions or blow-ups associated with firefighter fatalities and accidents [37]. In this study, the prescribed fire was conducted in a steep canyon under hot, dry conditions to investigate extreme fire dynamics specific to such terrains. It was part of CAL FIRE's Vegetation Management Program, which reduces wildfire fuel hazards using prescribed fire and mechanical methods on State Responsibility Area lands.

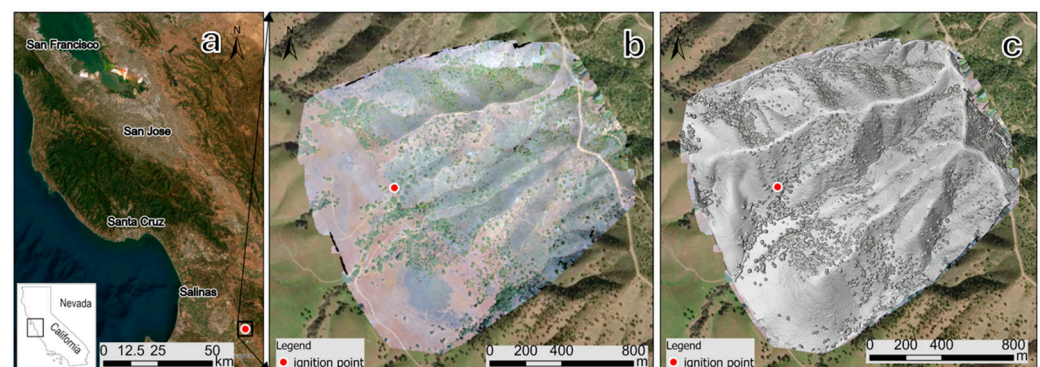


Figure 1. Study site: (a) location of the study site; (b) pre-fire UAV RGB orthomosaic with satellite imagery as the basemap; and (c) hillshade map derived from the UAV DSM.

Figure 1 illustrates the location of the prescribed fire and includes a high-resolution visible-spectrum drone mapping orthomosaic taken before the event. This location was particularly suitable for observing fire behavior in maritime chaparral due to its varied canyon topography and fuel distribution while allowing for a safe head fire (Figure 1b).

Pretreatment of the surrounding lands at the selected private ranch (Figure 1c) enabled the CAL FIRE unit to contain the fire within the canyon. Site selection was further supported by the San Benito-Monterey Unit's experience with prescribed burns and by the landowner's consent for research activities. The fire was ignited at the bottom of the canyon. The study site was equipped with Remote Automatic Weather Stations (RAWSs) and employed a remote-sensing approach to monitor fire behavior. Aerial remote sensing was conducted using drones and helicopters before, during, and after the fire.

The steep canyon terrain made the study site well-suited for observing fast-moving fire spread. The site exhibits varied fuel distribution, with maritime chaparral on south-facing slopes and denser oak trees on north-facing slopes. This distribution represents typical California coastal vegetation [38]. Consequently, this site is an ideal location for wildfire experiments aimed at replicating the most hazardous wildfire terrain conditions in California's essential ecosystems.

3. Materials and Methods

The methodological workflow consisted of five main steps: (1) UAV RGB and multi-spectral imagery were collected before the fire, one month after the fire, and six months after the fire; (2) the UAV imagery was processed into orthomosaics and DSMs, and the post-fire DSMs were calibrated using stable tie points and a linear regression model; (3) fuel-height loss and post-fire height gain were calculated by differencing calibrated DSMs across survey dates; (4) pre-fire multispectral imagery and field observations were used to classify fuel types; and (5) statistical models were used to evaluate relationships among UAV-derived fuel-height change, fuel type, remaining twig diameter, and maximum recorded temperature.

3.1. UAV Data Collection and Photogrammetric Processing

Drone flights were conducted on 27 July 2022, before the prescribed fire, on 21 November 2022, one month after the fire, and on 7 April 2023, six months after the fire to capture RGB and multispectral imagery under favorable weather, visibility, and lighting conditions where possible. Specifically, Phantom 4 and Inspire 2 drones (DJI Technology Co., Ltd., Shenzhen, China) were equipped with RGB and MicaSense 10-band sensors (MicaSense Inc., Seattle, WA, USA). These sensors enabled the capture of a wide spectral range, from near-infrared (NIR) to coastal blue wavelengths. The Phantom 4 drone, with its 1-inch 20 MP CMOS sensor, provided high-resolution mapping data at a spatial resolution of 9 cm. Meanwhile, the Inspire 2 drone, equipped with a MicaSense 10-band dual-sensor, collected multispectral data. This advanced sensor system, featuring two synchronized sensors, captured images across ten spectral bands, including both visible light and NIR. The multispectral data supported fine-scale image classification and vegetation differentiation, combined with in-field spectral signatures to create a detailed fuel type map for the entire area. The UAV images depict vegetation cover, and the accuracy of derived shape and elevation estimates depends on viewing geometry, including zenith and azimuth angles. In this study, UAV mapping flights were controlled by an autonomous application to maintain consistent flight paths and acquire nadir-view imagery across survey dates. The high-resolution images obtained were stitched together to produce RGB orthomosaic maps covering a site area of 1400 by 1500 m. To improve image quality while maintaining battery efficiency, the image overlap was set to 75% across flights, resulting in mapping coverage that exceeded the area of interest.

Ground control points (GCPs) were obtained from prominent, non-flammable, and immovable ground features that remained unaffected during the fire. We employed a Trimble R1 Modular Receiver, which supports the Global Navigation Satellite System

(GNSS), to achieve high-precision GCPs for drone image registration. GNSS can improve positioning accuracy and reliability relative to GPS-only measurements by incorporating multiple satellite constellations, including GPS, GLONASS, Galileo, and BeiDou. These GNSS-compatible devices also function where GPS signals are weak or unavailable.

These RGB image datasets were processed using Drone2Map software (Esri Inc., Redlands, CA, USA; 2023) to produce 2D and 3D geospatial data products, including multispectral orthomosaic maps (including RGB bands), as well as DSM and Digital Elevation Models (DEM) derived from a Structure-from-Motion Multi-View Stereo (SfM-MVS) algorithm. The photogrammetry method was employed to generate DSMs for both pre- and post-fire conditions. These high-resolution orthomosaic maps were further georeferenced using GCPs collected with a Trimble GNSS system on the same day. With the drone's GPS capabilities, the high-resolution RGB mapping achieved a spatial resolution of approximately 9 cm and location accuracy ranging from 0.5 to 1 m. The GNSS-measured GCPs improved the estimated orthomosaic positional accuracy to approximately 0.3–0.5 m. The georeferenced pre- and post-fire time-series maps enable the analysis of burned and unburned areas and changes in fuel height and species.

Initial comparison of the pre- and post-fire DSMs revealed angular mismatch and systematic elevation offsets, with a linear displacement from the valley bottom to the ridge top. Because terrain elevation is effectively invariant over the short interval between acquisitions, the DSMs were co-registered to remove these angular and vertical errors, which enabled subsequent analysis of fuel-height changes.

3.2. DSM Calibration

The accuracy of the drone mapping conducted in July 2022 was verified using GCPs collected by high-performance Trimble GNSS. This pre-fire mapping, free from the disturbances of shadows and fire effects, demonstrated high accuracy in depicting elevation. The images were collected under optimal weather and lighting conditions, including high visibility, slight overcast conditions that diffused sunlight evenly, and flights conducted near solar noon, resulting in clear images with minimal shadowing and low elevation error between the data and true elevation. This pre-fire DSM was georeferenced using GCPs.

Angular and vertical offsets in the DSMs were corrected using a Python-based workflow (Python v3.13.3) that combined linear regression in scikit-learn (v1.6.1) with geospatial processing via OSGeo/GDAL (v3.11.0) and array operations in NumPy (v2.2.6) and pandas (v2.2.3). Initially, the DSMs were clipped to a uniform area of interest, and the transformation method was validated. Pixel coordinates were then reassigned, and tie points from the pre-fire DSM were extracted to serve as training data. Using this data, a linear regression model was developed and trained to predict post-fire elevations. The predicted elevations were georeferenced and assigned the same coordinate system and projection. Finally, a new GDAL dataset was created to store the predicted elevations, ensuring an accurate comparison of the DSMs for detailed analysis of vegetation changes and other post-fire effects. The workflow of these steps is illustrated in Figure 2.

3.2.1. Extracting Tie Points as Training Data

A uniform analysis mask was applied to the DSMs for consistency. The drone flight plans, executed using the DJI GoPro app, covered the same area for each session, but variations in wind and battery life caused deviations in flight paths. As a result, the processed orthomosaic maps differed in coverage. Clipping the DSMs to a common area across all time points ensures uniformity, which is crucial for data calibration using machine learning algorithms and further fuel analysis. Additionally, clipping eliminates marginal

errors from orthomosaic maps, ensuring data integrity for subsequent calibration processes. The clipped area selection maximizes data coverage.

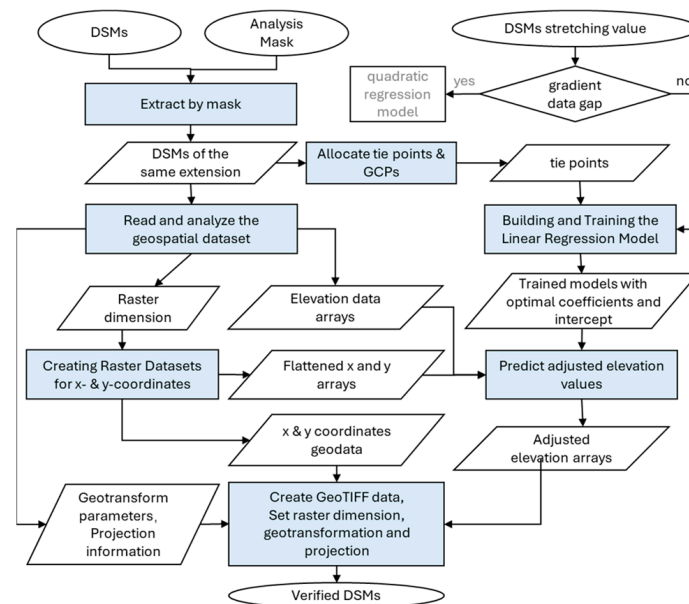


Figure 2. Workflow for DSM data calibration.

A total of 26 tie points, including four GCPs surveyed in situ, were used as training data for the DSM calibration model. The four GCPs were included only in the training dataset and were not used as independent validation points. These points were derived from pixels corresponding to stable land features whose elevations were not altered by the fire. This selection minimized potential biases associated with fuel-height loss during the burn and subsequent regrowth, thereby maintaining consistency between pre- and post-fire conditions. Ideal locations for these training data included the centers of bare earth patterns, large rocks, and trails, as these features are less likely to experience elevation changes. Unlike conventional tie points used for georeferencing, which typically involve turning points at road intersections or architectural features, this study employed the center pixels of prominent natural landmarks, such as large rocks and trail midpoints. The selected features were strategically chosen to maintain consistent elevation throughout the prescribed fire, ensuring accurate georeferencing under experimental conditions. Sharp elevation gradients along rock edges and trail boundaries can produce substantial pixel-level elevation differences. Aligning identical features across different maps can introduce alignment errors; as a result, the use of boundary elevation tie points may lead to significant errors. Additionally, selecting the center of the rocks mitigated errors caused by shadows and suboptimal lighting conditions. Figure 3 illustrates examples of the training data locations, highlighting the diverse land cover types used to ensure the model's effectiveness. The tie points were evenly distributed within the clipped DSM area from the valley bottom to the ridge top (Figure 3g). This spatial distribution allowed the regression model to capture the broad-scale linear elevation offset across the canyon terrain. Because the tie points were selected from stable, non-flammable landscape features, including large rocks, bare soil patches, and trail centers, their elevations were expected to remain unchanged before and after the fire. Therefore, the number and distribution of tie points were sufficient for correcting the dominant first-order DSM tilt. The training data were entered into the algorithm to train the prediction model, allowing it to maintain the pixel values that represent elevation accurately.

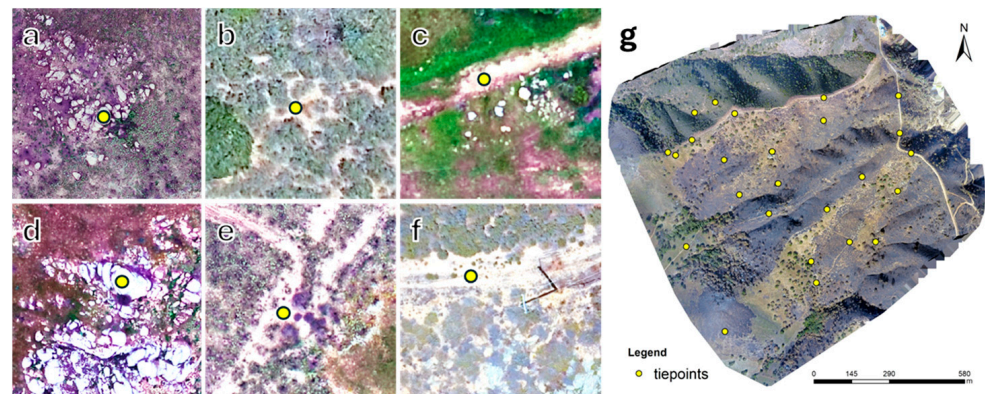


Figure 3. Examples of tie points and the distribution map. (a,d) Tie points on big rocks; (b,e) tie points on bare soil; (c,f) tie points at the center of trails; (g) Distribution of tie points, with post-fire UAV RGB orthomosaic imagery as the base map.

3.2.2. Reassigning Pixel Coordinates

The rasters were re-referenced using pixel-based coordinates (i.e., row–column indices) to improve computational efficiency. In this system, the x-coordinate begins at 0 in the leftmost column and increases by 1 across columns, while the y-coordinate starts at 0 from the top row and increases downward. The following equations were used to calculate these indices.

Column coordinate:

$$Y = \text{Int} (\text{Abs}((X - X_0)/Z) + 1)$$

Row coordinate:

$$X = \text{Int} (\text{Abs}((Y - Y_0)/Z) + 1)$$

where X and Y represent the raster's origin, X_0 and Y_0 are the coordinates of the pixel, and Z is the pixel size.

3.2.3. Surface Linear Regression Model and Elevation Calibration

The relative elevation differences among corresponding pixels were consistent across DSMs, indicating that the observed displacement was primarily linear and could be modeled as a first-order transformation. Therefore, elevation calibration was performed using linear regression, in which corrected elevation was modeled as the dependent variable and pixel coordinates and uncorrected elevation values were used as independent variables.

Tie points with x-coordinate, y-coordinate, true elevation, and uncorrected elevations from each DSM were read and converted to NumPy arrays as input to train the regression model. A linear regression model was trained using tie points to adjust the DSM in November, determining the best-fit plane that minimizes the difference between true and tilted elevation values. The x- and y-coordinates of the tie points were used as independent variables, and the known elevation values were used as the dependent variables. There are two key coefficients in the linear regression model. First, the regression coefficients represent the slope of the fitted line or plane and indicate how elevation changes with x-coordinate, y-coordinate, and initial elevation. Second, the intercept represents the baseline elevation when all independent variables are zero. The same process was repeated to build and train the model for the April DSM.

The input data, which consisted of DSMs from pre-fire (sampled in July 2022), post-fire (sampled in November 2022), and six-month post-fire (sampled in April 2023), with x- and y-coordinates, were read into arrays and flattened to create a suitable input format for the regression model. The trained linear regression model predicted elevation values for every pixel with the given coordinates within the raster. After adjustment, the elevation

data in a long array format was converted into a GeoTIFF file and was assigned the same dimensions, geotransform, and projection as the original raster. These adjustments were executed for the November DSM and the April DSM separately.

DSM calibration accuracy was evaluated using 11 independent validation points selected from stable, visually identifiable landscape features, including large rocks, bare soil patches, and trail surfaces, that were not used for model training. Elevation differences between the pre-fire DSM and each post-fire DSM were calculated at these validation points before and after calibration, and RMSE was used to quantify calibration improvement.

3.3. Fuel-Type Classification

To conduct a more comprehensive analysis of fuel-height changes, a pre-fire vegetation-cover map was generated using high-resolution pre-fire UAV multispectral imagery and in situ ecological data. The UAV imagery captured in July 2022 documented pre-fire vegetation conditions and covered the sampling transects used for in situ ecological surveys before the prescribed fire. Species data recorded with GPS coordinates were accurately georeferenced to the UAV imagery and served as ground truth data for the supervised classification. Thus, the July imagery was selected for classification.

The pre-fire UAV imagery was processed into a False Color Infrared (CIR) composite map and was subsequently used for classification. It was further segmented into objects by grouping spatially adjacent pixels with similar spectral characteristics. The segmentation process was based on the Mean Shift approach and conducted in ArcGIS Pro (version 3.4). The spectral resolution was set at 18 out of 20, and the spatial resolution at 13 out of 20, with a minimum of 20 pixels per segment. RGB imagery was then segmented similarly as a supplementary reference. This approach aimed to improve the model's ability to differentiate between plant species that are closely clustered and exhibit similar spectral characteristics without causing false splits within the same species, while balancing fine-scale segmentation against classification noise [39].

The training data for image classification were a combination of in situ survey data and visually interpreted features identified directly from the UAV imagery. The in situ species data were systematically collected pre-fire along 10 transects, every 50 m in length, using the ecological line-intercept method and georeferenced with GNSS [40]. They were aligned with segmented features on the CIR map as the primary training data. Then, experienced ecologists manually identified vegetation species and other land cover types on the segmented CIR imagery to generate supplementary training data, using RGB as a reference for training data development. This process established a training dataset with 10 to 20 selected objects per land cover type. The cover types encompassed key species of the maritime chaparral, including *Arctostaphylos* spp. (manzanita), *Salvia mellifera* (black sage), *Quercus* spp. (oak trees), *Adenostoma fasciculatum* (chamise), *Ceanothus* spp. (California lilac), and other shrubs. Herbaceous plants that lacked distinctive identification features or were too small to be classified individually were grouped into a single category. Dry and dead herbaceous vegetation, which exhibited spectral characteristics similar to barren and rocky areas, was grouped within the same classification category. The training dataset comprised 170 labeled objects.

A supervised, object-based classification method was utilized, employing the K-nearest neighbor algorithm. Reference data were created along the transects based on the in situ ecological survey and supplemented by visually identified features distributed along the canyon to reduce bias. In total, 509 reference points were created randomly within the reference data, validating all eight classes. After comparing the classified pixels with the reference truth data, producer's accuracy (PA) and user's accuracy (UA) for each class were calculated to evaluate class-specific classification performance. Overall accuracy (OA)

was computed as the sum of correctly classified pixels for all classes divided by the total number of reference (ground truth) pixels. Cohen's Kappa was calculated based on the OA and the random expected agreement to further account for random agreement.

$$\text{Kappa} = (\text{OA} - \text{Pe}) / (1 - \text{Pe})$$

Pe = random expected agreement.

$$\text{Pe} = \sum (N_{i+} \times N_{+i}) / N^2$$

N_{i+} = total number of reference points for class i ,

N_{+i} = total number of classified points for class i ,

N = total number of reference points, which was 509 in this study.

3.4. Helicopter Thermal Survey and Field Twig-Diameter Measurements

During the fire, a helicopter equipped with San José State University's Wildfire Infrared Imaging System (SWIS) flew at an altitude of 1200 feet (365 m) above ground level (AGL). Continuous temperature data were collected for approximately 12 min during the prescribed fire and subsequently processed. These data were used for exploratory comparison with UAV-derived fuel-height loss.

One year after the prescribed fire (October 2023, with supplementary sampling in spring 2024), we sampled the remaining twig diameter of residual fuel using rulers or calipers in situ across 27 plots, including 574 twigs from 149 shrubs. This sampling followed "Method 1" described in [41] and was used as a field-based indicator of spatial patterns in fire effects. We located plot centers with a sub-meter-accurate Trimble R1 GNSS Receiver (Trimble Navigation Limited, Westminster, CO, USA; 2016) and selected shrubs within approximately 2 m of each center. At this site, the remaining twig diameter (0.0–50.0 mm) of black sage, chamise, and unknown shrub species has been shown to correlate with fire intensity and fire severity, with larger remaining twig diameters indicating greater consumption of finer twigs [41]. Because detailed fire-behavior parameters such as residence time, flame height, flame length, and fine-fuel moisture were not available for this analysis, twig diameter was interpreted as an indirect field-based indicator of fire effects rather than a standalone measure of fire intensity. We statistically modeled remaining twig diameter using a generalized linear mixed model (GLMM) to assess its relationship with UAV-derived fuel-height consumption, with random intercepts for species and nested random effects for plot and shrub [42]. A Gamma error distribution with a log link was selected because twig diameter is a positive, continuous response variable, and this structure ensured positive fitted values and improved model convergence. Statistical analyses were performed in R (v4.3.0; R Core Team, 2023) within the RStudio environment (v2023.06.0; Posit Software, 2023).

$$\gamma \sim \text{FuelHeightCons} + (1 \mid \text{species}) + (1 \mid \text{plot/shrub})$$

where γ is twig diameter (mm); FuelHeightCons is the UAV-derived fuel-height consumption, i.e., the height change at the pixel corresponding to the sampled shrub; $(1 \mid \text{species})$ is the random intercept for species, and $(1 \mid \text{plot/shrub})$ represents shrubs nested within the plot.

The model was fitted using the `glmer()` function in the `lme4` package in R. Model diagnostics did not indicate overdispersion or other major violations of assumptions.

4. Results

4.1. UAV Orthomosaic Maps and Fuel Classification

The pre-fire, 1-month post-fire, and 6-month post-fire RGB orthomosaic maps are shown in Figure 4. The high-resolution RGB mapping achieved a spatial resolution of

9 cm. The pre-fire RGB map (Figure 4a) resolved individual vegetation patches and bare soil among shrubs and trees. It also distinguishes different fuel types. In contrast, the post-fire RGB map (Figure 4b) shows the spatial extent of burned areas. Most shrubs experienced top kill, with little remaining aboveground structure. In the intensely burned areas, large trees exhibited blackened, charred branches, but their locations and main structures remain intact. Some oak trees remain mostly green with a slightly reduced canopy cover, indicating partial canopy consumption during the fire. The 6-month post-fire map (Figure 4c) illustrates vegetation regrowth during the rainy winter of 2022 and spring of 2023. During this period, the abundant precipitation led to significant vegetative recovery and substantial increases in plant elevation. Although the unburned areas exhibit greater green vegetation cover compared to the burned regions, new green sprouts emerged throughout the burn unit. Notably, certain shrubs and trees in the burned areas displayed green sprouts, suggesting post-fire resprouting or survival.

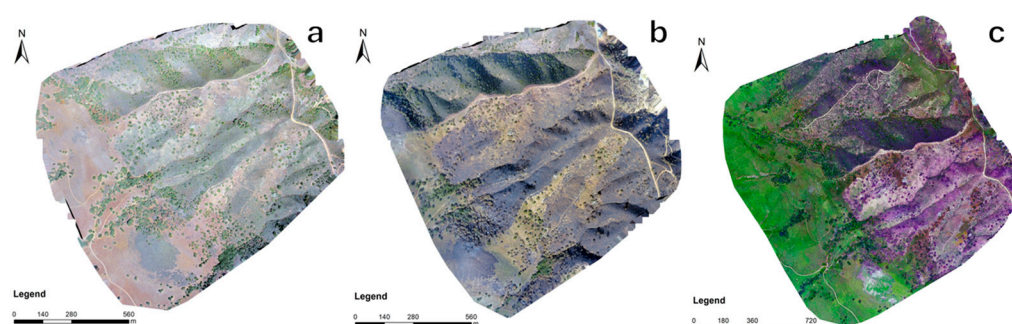


Figure 4. RGB orthomosaic maps generated from UAV imagery collected (a) pre-fire, (b) one-month post-fire, and (c) six months post-fire.

The land cover classification map (Figure 5) illustrates the distribution of plants pre-fire. With boundaries precisely distinguishable from other vegetation, oak trees were sparsely distributed on the south-facing slope, with denser concentrations observed within the canyon drainage. Black sage, chamise, and California lilac are the dominant shrub species and coexist within the site. Cohen's kappa for the vegetation classification was 0.82, and overall accuracy was 0.93, indicating reliable classification performance. The barren soil and rocks were accurately classified with a PA of 0.97. The manzanita and oak trees showed higher PAs of 0.91 and 0.97, respectively. Although the classification showed strong overall performance, shrub species were more difficult to separate because of overlapping spectral characteristics. The producer's accuracy was 0.80 for California lilac and 0.74 for black sage, but only 0.26 for chamise; therefore, species-level results involving chamise should be interpreted cautiously. This high-resolution vegetation classification was applied in the analysis of fuel dynamics, incorporating UAV-based DSMs.

4.2. Estimation of Fuel-Height Changes

Validation using 11 stable validation points showed that DSM calibration substantially reduced elevation error. RMSE decreased from 97.103 m to 0.188 m for the July–November comparison and from 40.873 m to 0.132 m for the July–April comparison.

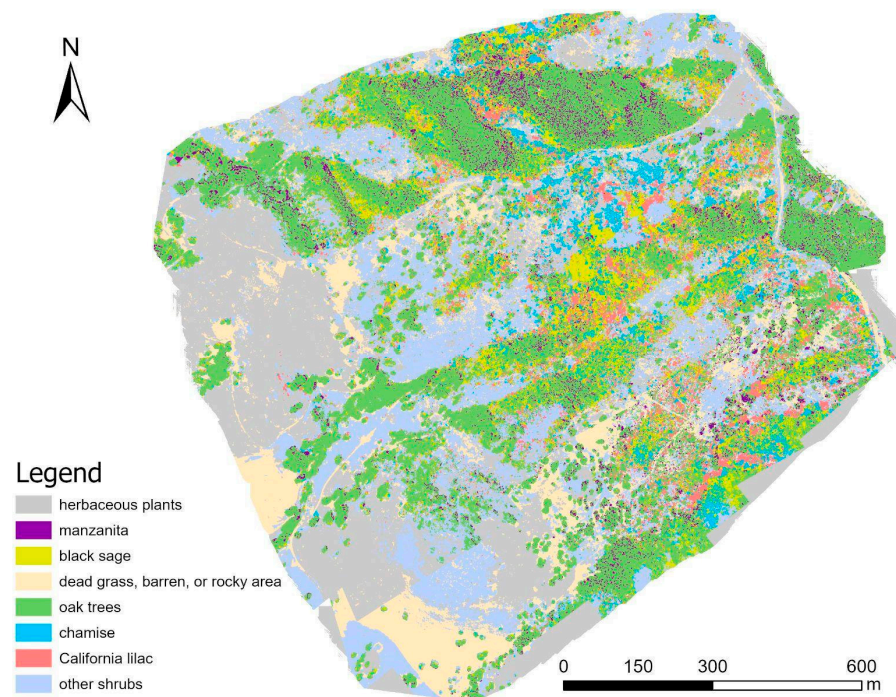


Figure 5. Pre-fire land cover classification, showing fuel distribution.

Raster calculations were applied to the calibrated DSMs by subtracting the 1-month post-fire DSM from the pre-fire DSM, producing calibrated fuel-consumption estimates (Figure 6a). The map illustrates areas where fuel-height decreased (in red) and increased (in blue) in the unburned area due to plant growth between the two mapping flights. White indicates no elevation change. By visually comparing the fuel-height map and the RGB 1-month post-fire map (Figure 6c), it is evident that high-resolution drone images facilitate the estimation of fuel-height loss at the individual-plant scale. Some oak trees appear red in Figure 6a, indicating significant vegetation loss due to the fire. Notably, many large trees appear as red circles rather than solid red shapes, indicating that only the canopy margins were burned, while the centers remained unburned. In addition to the fuel-height loss of oak trees, light reddish areas reveal the consumption of shrubs or dry grass. By comparing the blue negative-value in Figure 6a, with the 1-month post-fire map (Figure 6c), one can precisely observe that the blue areas correspond to the unburned areas, where the unburned vegetation retains its original color, easily distinguishable from the charcoal-colored burned areas. The burned land area appears green in Figure 6b, indicating regrowth and gain in the height of vegetation between November 2022 and April 2023, attributed to post-fire regrowth and sprouting during the spring. The high-resolution UAV-based DSM can accurately resolve fine-scale unburned patterns, such as the narrow unburned strip between two large burned areas at the bottom left corner.

4.3. Relationship Between Fuel-Height Changes, Fuel Type, Fire Severity, and Temperature

4.3.1. UAV-Derived Fuel-Height Dynamics by Fuel Type

Fuel-height loss, regrowth, and plant-classification values were extracted using a 5 m sampling grid. The distribution of fuel-height loss and regrowth data across various fuel types illustrates the fuel dynamics (Figure 7a). Oak trees and manzanita exhibited higher fuel-height loss compared to other fuel types, particularly shrub classes. Compared with black sage and California lilac, oak trees showed a larger range of height loss during the fire. Samples located near the centers of oak canopies showed less height loss because these areas were rarely completely burned during the fast-moving canyon fire, whereas canopy

margins often burned more completely. The margin often burned completely, resulting in a significant decrease in height [43,44].

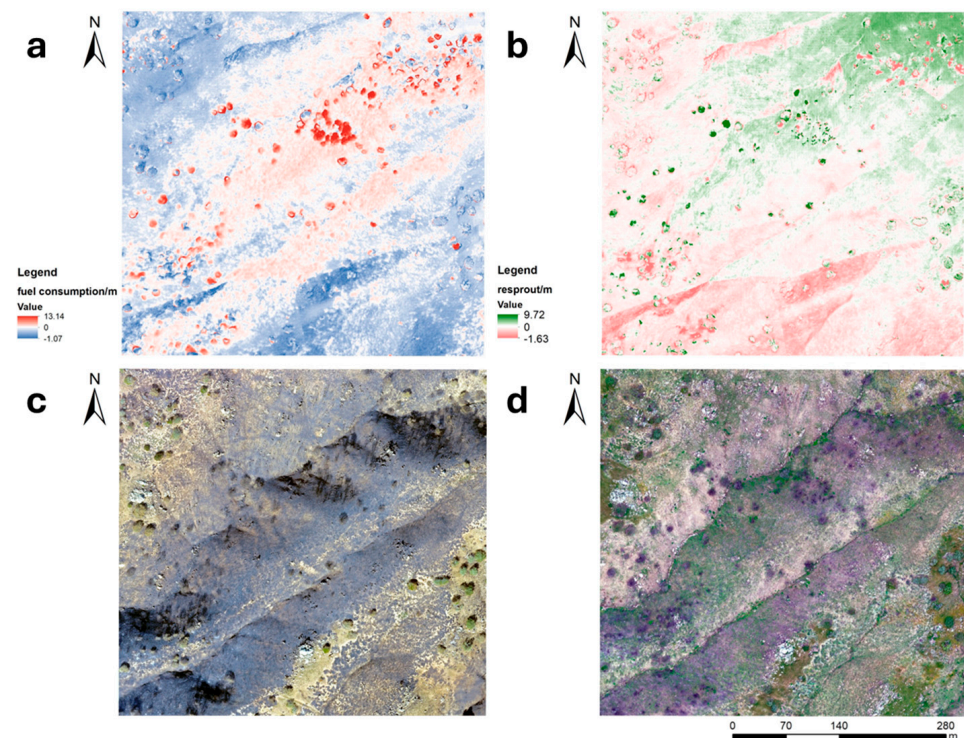


Figure 6. Adjusted fuel dynamics: (a) fuel-height loss, (b) six-month post-fire fuel-height gain, (c) one-month post-fire RGB orthomosaic, and (d) six-month post-fire RGB orthomosaic of the same observing area.

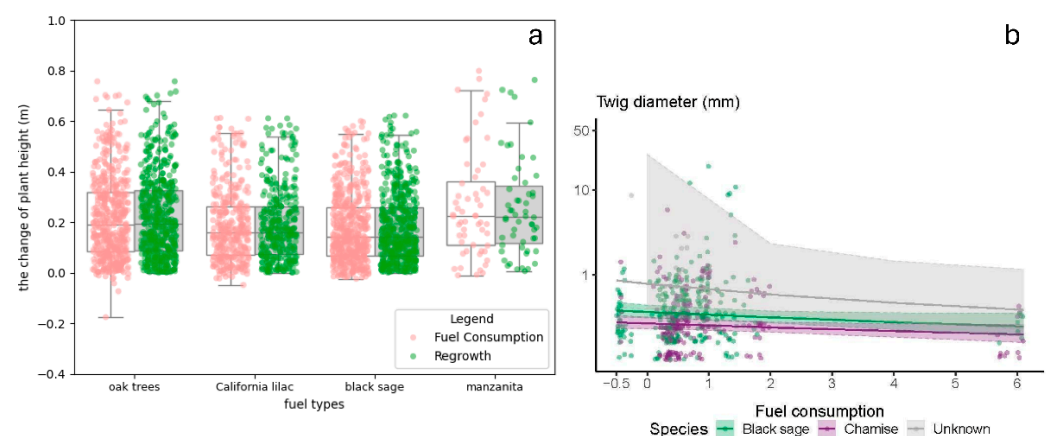


Figure 7. (a) Fuel dynamics of different fuel types; (b) remaining twig diameter (mm) was related to UAV-derived fuel-height consumption values (m). Lines are model predictions, ribbons are 95% confidence intervals, and dots represent raw data, with a small amount of jitter to aid visualization.

Black sage and California lilac show a relatively small decrease in height. This aligns with their characteristics as shrub vegetation. Their reduction in height, compared to their average height in California (1–2 m) [45], indicates that most were burned to the ground. This is consistent with previous studies in chaparral, where shrubs like black sage, California lilac, and chamise are associated with high fire severity and near-complete loss of aboveground biomass [46,47].

4.3.2. Relationship Between UAV-Derived Fuel-Height Change and Remaining Twig Diameter

UAV-derived fuel-height change was significantly related to observed remaining twig diameter, suggesting that DSM-derived structural change captured some variation associated with field-observed shrub consumption (Figure 7b, $p < 0.05$, marginal $R^2 = 0.185$, conditional $R^2 = 0.852$). The marginal R^2 indicates the variation explained by UAV-derived fuel-height change alone, whereas the conditional R^2 indicates the variation explained by the full model, including species and plot/shrub-level random effects. As the fuel-height loss increased, twig diameters decreased. Species had statistically distinct remaining twig diameters ($p < 0.05$). The magnitude of difference was small and likely not ecologically significant (modeled fit values between species were within 1 mm of each other). Model diagnostics did not indicate major violations of assumptions (e.g., overdispersion or multicollinearity; all VIF < 1.02) [48].

4.3.3. Comparison Between UAV-Based Fuel-Height Changes and Temperature

Table 1 summarizes separate ordinary least-squares linear regression models evaluating post-fire height change in relation to fuel-height loss and, separately, exploratory relationships between UAV-derived fuel-height loss and maximum recorded temperature. Separate ordinary least-squares linear regression models were fitted for each fuel type. Sample size represents the number of 5 m grid sampling points assigned to each fuel type within the classified vegetation map shown in Figure 5. The results indicate strong positive relationships between fuel-height loss and the regrowth for all four species, with R^2 values ranging from 0.545 for black sage to 0.996 for California lilac. During the fast-moving canyon fire, oak trees showed limited fuel-height loss overall, with a marked increase in canopy consumption at elevated temperatures. In contrast, black sage exhibited a statistically significant correlation, although the R^2 value of 0.545 reflects only a moderate relationship [8,49]. California lilac and manzanita also showed strong and statistically significant relationships between fuel-height loss and post-fire height change.

Table 1. Linear regression results for relationships among UAV-derived fuel-height loss, post-fire height change, and fire temperature by fuel type.

Fuel Type	Sample Size	Fuel Regrowth vs. Fuel-Height Loss			Fuel-Height Loss vs. the Highest Temperature		
		R^2	SE	p -Value	R^2	SE	p -Value
black sage	1038	0.545	0.016	<0.001	0.004	0.0001	0.044
oak trees	1059	0.903	0.010	<0.001	0.014	0.0003	<0.001
manzanita	106	0.953	0.019	<0.001	0.031	0.0008	0.071
California lilac	658	0.996	0.003	<0.001	0.007	0.0001	0.032

In contrast, the linear relationship between the fuel-height loss and maximum recorded temperature was weak for the examined plant species, with low R^2 values despite statistically significant p -values for several fuel types, indicating that maximum temperature explained only a small proportion of the observed variation in fuel-height loss. Therefore, the temperature comparison should not be interpreted as evidence that the maximum recorded temperature is a reliable indicator of fire intensity or fuel-height loss.

5. Discussion and Conclusions

The GLMM results indicate that UAV-derived fuel-height consumption was associated with field-measured remaining twig diameter, a ground-based indicator of fire effects in chaparral shrubs. When combined with plot- and shrub-level heterogeneity, the model explained most of the observed differences. These findings support the UAV-based fuel-

dynamics estimation method by demonstrating its relationship to on-the-ground fire-severity indicators, while also highlighting the added value of accounting for species.

The exploratory comparison between UAV-derived fuel-height loss and the maximum recorded temperature produced several statistically significant slope terms but consistently low R^2 values, indicating that the maximum temperature explained only a small proportion of the variation in fuel-height loss. These results suggest a statistically detectable association, rather than a strong ecological or operational predictor. Fuel-height loss was likely influenced by additional factors not captured by maximum temperature alone, including fuel structure, species composition, canopy geometry, slope position, local wind exposure, fuel moisture, and fire residence time [49–51]. This study did not reconstruct the full temporal and spatial variability of fire behavior during the prescribed burn. Therefore, the UAV-derived results should be interpreted as pre- and post-fire vegetation structural change rather than as a direct reconstruction of fire intensity.

The circular pattern of fuel loss observed in oak trees, alongside post-fire RGB images, supports previous studies identifying factors contributing to less intense fire behavior under oak canopies. Oak canopy shade can inhibit under-canopy vegetation growth and fine-fuel accumulation, and the lack of ladder fuels can prevent flames from being carried into the canopy [50,51]. Additionally, the shade slightly increases soil humidity, reducing ignition likelihood [52]. Fire resistance correlates positively with bark thickness and tree diameter [53–55]. Native oaks possess thick bark that insulates cambium cells from heat and helps prevent surface fires from climbing the trunk [56].

Areas with higher fuel-height loss exhibited greater post-fire elevation increases and more substantial vegetation regrowth than unburned areas. These strong relationships are unlikely to be primarily caused by DSM processing effects because calibration was evaluated using independent stable validation points and showed substantial RMSE reduction. However, seasonal vegetation dynamics, species-specific regeneration patterns, and residual spatial autocorrelation may still influence the observed patterns. This aligns with previous studies on chaparral succession [57–60]. This positive relationship across species suggests that areas with greater canopy consumption tend to exhibit stronger post-fire recovery, consistent with resprouting-driven dynamics. This response is expected in fire-dependent vegetation communities of California, where many chaparral plants have adapted to fire through mechanisms such as resprouting from roots or stems and producing seeds that germinate in response to fire cues [61]. In addition to these regeneration pathways, post-fire conditions can directly favor vigorous growth: combustion releases nutrients back into the soil [62,63], and the removal of existing vegetation reduces competition for light, water, and nutrients, thereby facilitating the establishment and expansion of new growth [64,65]. The regrowth observed in our study likely reflects a combination of recovery of burned individuals and the establishment of new plants stimulated by heat and smoke cues and facilitated by reduced competition. However, post-fire regeneration can also involve changes in species composition relative to pre-fire conditions, which may lead to the misidentification of new sprouts at the species level in both field observations and UAV-based mapping. Although DSM calibration reduced broad-scale angular and vertical offsets, local uncertainty may remain in the UAV-derived height-change estimates resulting from shadows, illumination differences, post-fire ash or charred surfaces, and photogrammetric artifacts. These factors may reduce feature-matching quality in localized areas, particularly within shaded vegetation patches or low-texture burned surfaces, leading to localized overestimation or underestimation of fuel height. Therefore, the results should be interpreted as DSM-derived fuel-height change rather than direct biomass consumption, with greater confidence placed on broader spatial patterns and relative differences among fuel types than on individual-pixel values.

In situ height measurements of burned shrubs have previously been used to infer fire severity [66,67]. In situ twig-diameter measurements of chamise and black sage serve as an ecologically relevant and validated proxy for fire severity. Both UAV-derived fuel-height change and post-fire twig diameter describe different aspects of fire effects on vegetation structure. Their association at this study site supports the use of UAV-derived height change as a complementary structural metric, but not as a direct substitute for established fire-intensity or fire-severity measurements. We found that UAV-derived shrub height change relates to in situ post-fire twig-diameter measurements, an accepted proxy for fire severity. This differs from research that found a remotely sensed metric of fire severity, dNBR, did not relate to maximum plant skeleton height sampled in situ at a chaparral study site in Malibu, California [67]. In addition to UAV imagery, airborne LiDAR data were collected before and after the prescribed-fire experiment. The LiDAR scanning data provided high-resolution point-cloud data for terrain-surface characterization. However, at this canyon site, the north-facing slope introduced elevation discrepancies in the LiDAR data, limiting its application for large-scale fuel-height loss estimation. Further research may provide insights into the accuracy of fuel-load estimation using LiDAR and UAV data.

Fire agencies could apply this workflow for prescribed-fire monitoring by collecting UAV imagery before and after a burn, generating orthomosaics and DSMs, calibrating DSMs with stable ground features, and comparing fuel-height and vegetation-cover changes across fuel types. This approach requires a mapping UAV, RGB or multispectral sensors, GNSS or stable reference points, and standard photogrammetry software. Compared with intensive field surveys or airborne LiDAR, it can provide rapid, spatially continuous information for fuel-treatment evaluation and post-fire recovery monitoring, although field observations remain important for validation and interpretation.

In regions with high wildfire risk, fire and land managers need tools to quantify hazardous fuel reduction, track post-fire community succession, assess changes in species composition and biomass, and evaluate how fuel treatments alter future fire risk. UAV-derived fuel-dynamics estimates, therefore, provide a powerful, easy-to-deploy tool to support these management objectives.

We developed and implemented a comprehensive protocol for estimating individual-plant-scale fuel-height loss using UAV imagery captured before and after the prescribed fire. This methodology enables the analysis of fuel-height loss and vegetation regrowth at a fine individual-plant scale, contributing insights into ecological and fire management concerns. By accurately adjusting the DSMs across different time series using tie points and a surface linear regression model, we addressed the tilting problem in UAV-based DSMs and estimated the change in vegetation height at the site from pre- to post-fire conditions with high precision and resolution. The resulting fuel-height dynamics dataset provides a foundation for future long-term time-series analyses. However, the workflow involves limitations, including localized DSM uncertainty, shadow and post-fire surface effects, and the site-specific nature of this prescribed canyon fire experiment. The integrated analysis provided insights into relationships among UAV-derived vegetation structural change, fuel-height loss, fuel type, field-based fire-severity indicators, and post-fire vegetation recovery. UAVs provide a flexible platform for high-resolution characterization of post-fire vegetation structural change, vegetation recovery, and species-level patterns. The approach is also suitable for repeated mapping and long-term monitoring of post-burn effects, ecological succession, and changes in fire risk. This protocol can further support cross-disciplinary wildfire research on greenhouse gas and aerosol emissions, carbon stocks, vegetation recovery, and fire-behavior analysis.

Author Contributions: X.R. led the conceptualization of the UAV-based analysis workflow, post-fire UAV data-collecting flights, UAV data processing, data analysis, and interpretation of results, and was the primary contributor to writing the manuscript and preparing figures. D.B. conducted in situ measurements and carried out fuel-type classification. J.A. and K.M.W. conducted in situ measurements, sampling, and a statistical analysis of the twig-diameter data and contributed to reviewing and editing the manuscript. K.M.W. also contributed to funding acquisition and initial project framing. C.B.C. contributed to the funding acquisition, initial project framing, led the canyon fire experiment, and collected and processed the remote temperature data. H.B. conducted UAV data-collection flights, in situ measurements, and sampling. B.Y. contributed to the funding acquisition, initial project framing, UAV flights, and manuscript revision. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The programming code used for DSM calibration is available at the GitHub repository below. UAV remote-sensing data are available from the corresponding author upon reasonable request. https://github.com/Xiangyusherry/CanyonFire_DSMverify (accessed on 15 June 2026). Open access to representative processed data products and sample files will be enabled on the same GitHub page once the pending privacy/data-sharing review is completed.

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Abbreviations

The following abbreviations are used in this manuscript:

CIR	Color Infrared
DEM	Digital Elevation Model
dNBR	Delta Normalized Burn Ratio
DSM	Digital Surface Model
DTM	Digital Terrain Model
GCP	Ground Control Point
GDAL	Geospatial Data Abstraction Library
GLMER	Generalized Linear Mixed-Effects Model
GLMM	Generalized Linear Mixed Model
GLONASS	Global Navigation Satellite System; Russian satellite navigation system
LiDAR	Light Detection and Ranging
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
OA	Overall Accuracy
OSGeo	Open Source Geospatial Foundation
PA	Producer's Accuracy
RAWs	Remote Automatic Weather Stations
RdNBR	Relative Delta Normalized Burn Ratio
RGB	Red, Green, and Blue

RTK	Real-Time Kinematic
SfM-MVS	Structure-from-Motion Multi-View Stereo
UA	User's Accuracy
UAV	Uncrewed Aerial Vehicle
VIF	Variance Inflation Factor

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