



REVIEW

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Methods and implications of canopy base height characterization for modeling crown fire potential

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Abstract

Canopy base height (CaBH; distinct from tree-level crown base height, CrBH) represents the lowest height at which canopy fuel, aggregated across multiple tree crowns, can propagate fire vertically and serves as an essential variable for modeling crown fire transition and hazard to inform fuel reduction treatment planning. However, as fire models have been applied to increasingly diverse forest structures and remote sensing technologies have advanced, a variety of methods for characterizing CaBH have emerged. Here, we review the primary approaches for CaBH characterization using field observation, airborne Lidar, and satellite-based mapping. We then apply these methods across four conifer forest types in northern New Mexico (USA) to evaluate how method choice and forest structure influence CaBH characterization and predicted fire behavior using a Rothermel-Van Wagner crown fire modeling framework. Our results show that CaBH characterizations vary widely among measurement methods (mean within-plot range = 6 m), and that these differences lead to substantial variation in predicted torching index (mean within-plot range = 14 km h⁻¹), demonstrating that method choice strongly shapes modeled crown fire hazard. Further, we found that divergence among methods increases with tree height variability. These results highlight the need for forest managers and fire behavior modelers to be deliberate in selecting and justifying their choice of CaBH characterization, particularly in structurally complex forests.

Keywords Canopy base height, Lidar, Satellite remote sensing, Fire behavior modeling, Forest structure, Crown fire hazard

Resumen

La altura de la base del dosel de un árbol (CaBH, que es diferente a la altura de la base de la corona del mismo árbol, CrBH), representa la altura más baja a la cual el combustible del dosel, agregado a través de múltiples doseles o copas de árboles en un rodal, puede propagar el fuego de manera vertical, y sirve como una variable esencial para modelar la transición a un fuego de copas y el peligro de incendio, y para informar sobre el planeamiento de tratamientos de reducción de combustibles. Sin embargo, como los modelos de fuegos (o modelos de incendios) han sido aplicados de manera incremental a diversas estructuras forestales, y las tecnologías que usan sensores remotos han ido avanzado, ha emergido como consecuencia una variedad de métodos para caracterizar CaBH. Revisamos aquí las aproximaciones primarias para caracterizar CaBH usando observaciones de campo, tecnología Lidar aerotransportada,

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y mapas basados en información satelital. Aplicamos luego esos métodos sobre cuatro tipos de bosques de coníferas en el norte de Nuevo Mexico (EEUU) para evaluar cómo la elección de un método y la estructura forestal, influyen la caracterización y predicción del comportamiento del fuego, usando el marco del modelado de fuegos de copa de Rothermel-Van Wagner. Nuestros resultados muestran que las caracterizaciones de CaBH variaron ampliamente entre los métodos de medición (la media dentro de un rango de cada parcela fue = 6 m), y que esas diferencias llevaron a una variación substancial en la predicción del índice de quemado (*torching index*), con una media dentro de un rango de cada parcela = 14 km h⁻¹, demostrando que la elección del método influye fuertemente en los resultados del modelado del riesgo de incendio de copas. Además, demostramos que la divergencia entre métodos se incrementa con la variabilidad en la altura entre los árboles. Estos resultados resaltan la necesidad, para los gestores de incendios y los que modelan el comportamiento del fuego, de que sean cautelosos al elegir y justificar su elección para la caracterización de las CaBH, particularmente en bosques estructuralmente complejos.

Introduction

Background

Fire exclusion, commercial timber practices, and historical overgrazing have increased tree density and fuel continuity in many seasonally dry forests across the western United States (US) while changing climate conditions have increased ecosystem flammability (Covington and Moore 1994; Jolly et al. 2015; Abatzoglou and Williams 2016; Goodwin et al. 2021; Kreider et al. 2024). Together, these factors have increased the extent of high-severity wildfires, heightening exposure and vulnerability for communities in the wildland–urban interface and eroding key ecosystem services such as carbon storage, water regulation, and timber production (Reid et al. 2016; Modaresi Rad et al. 2023; Wasserman and Mueller 2023). Ongoing efforts to characterize and mitigate wildfire risks to communities and ecosystems (U.S. Congress 2003, 2021a, b, 2023) depend, in part, upon fire behavior modeling to guide fuel hazard assessments, silvicultural treatment designs, and prescribed fire planning. Because these modeling systems used by land managers are partially driven by the vertical arrangement of fuels, accurately representing vertical forest structure is essential for effective decision-making and remains a primary source of modeling uncertainty.

One metric of particular importance in most common fire behavior modeling systems is canopy base height (CaBH), the lowest height above the ground at which there is sufficient fuel quantity to propagate the vertical spread of fire within the canopy. CaBH is a method-defined variable rather than an intrinsic stand property. At the tree-scale, CaBH is equivalent to crown base height (CrBH), the lowest height above ground with sufficient fuel to propagate the vertical spread of fire within an individual tree crown. Canopy base height and crown base height are both commonly referred to as CBH, but here we abbreviate them CaBH and CrBH to differentiate between them. At coarser scales (e.g., plot, 30 m raster pixel, stand),

CaBH reflects a fuel-continuity threshold that is often calculated by aggregating tree-level measures of CrBH or by modeling a canopy bulk density threshold. However, early thresholds were determined arbitrarily (e.g., Sando and Wick 1972) and the minimum fuel density necessary to propagate fire vertically has not been empirically tested, with proposed thresholds ranging from 0.011 to 0.067 kg/m³ (Alexander et al. 2004). CaBH was originally defined at coarse scales as the average CrBH within a stand as part of Van Wagner's (1977) crown fire transition model, which uses CaBH and foliar moisture to predict the critical surface fire intensity necessary to transition fire into the canopy. This transition criterion has since been linked with several other models, including Rothermel's surface and canopy fire spread models, to create an integrated system for predicting crown fire potential (Rothermel 1972; Rothermel 1991; Scott and Reinhardt 2001). As part of this framework, Scott and Reinhardt (2001) also defined two operational metrics of crown fire hazard: torching index, the 6.1 m (20 ft) open wind speed at which crown fire initiation is expected, and crowning index, the 6.1 m (20 ft) open wind speed necessary to sustain fire spread within the canopy. Open wind speed refers to wind measured over open terrain, without the influence of vegetation. This framework serves as the basis of many operational fire behavior models used to guide forest management throughout North America, including BehavePlus (Andrews et al. 2005), FARSITE (Finney 1998), FlamMap (Finney 2006), FSIM (Finney et al. 2011), and Prometheus (Tymstra et al. 2010).

Although CaBH in Van Wagner's (1977) model is defined as the mean CrBH, researchers have raised concerns about applying this model to structurally complex, uneven-aged forests, which span diverse forest types, fire regimes, and management priorities (Scott and Reinhardt 2001; Fulé et al. 2002). To address these concerns, researchers have developed alternative CaBH calculations (e.g., lower percentile of CrBH or canopy

bulk density thresholds) that diverge from mean CrBH and are more sensitive to lower canopy structure (Graham et al. 1999; Fulé et al. 2002; Reinhardt and Crookston 2003; Magalhães and Tomé 2026). While these alternative CaBH characterizations may better represent lower canopy structure in uneven-aged forests with high tree height variability, the greater heterogeneity in CrBH in such stands is also likely to increase disagreement in CaBH estimates and modeled fire behavior across characterization approaches.

The development of new fire modeling systems that require continuous maps of CaBH across large spatial extents has amplified the use of alternative CaBH definitions, leading to an increase in measuring and modeling CaBH using remote sensing (Keane et al. 2001). Remotely sensed CaBH products can be generated using active sensors (e.g., Lidar or radar) that transmit their own electromagnetic radiation, or using passive sensors (e.g., multispectral cameras) that record reflected solar radiation. Sensors can be deployed from a variety of platforms, including terrestrial, uncrewed aerial systems (UAS), crewed aircraft, and satellites. Data types include three-dimensional point clouds, waveforms, and imagery. Methods for calculating CaBH from remotely sensed data include both the aggregation of directly measured CrBH and identification of thresholds within continuous vertical fuel profiles. Maps of CaBH can be produced directly from remotely sensed data (e.g., Andersen et al. 2005) or indirectly through statistical models that predict CaBH from spatially explicit predictor data (e.g., Reeves et al. 2009; Hakkenberg et al. 2024). As such, the current approaches for characterizing CaBH span field-based measurements, remote sensing products, and model-based predictions, each with distinct assumptions, scales, and limitations. Despite the wide range of data sources and calculation methods now in use, few studies have evaluated how these choices influence CaBH estimates or predicted crown fire hazard across different forest types and conditions. Quantifying this variation can support forest management by identifying approaches that yield conservative estimates of canopy fuel height and crown fire potential to ensure characterizations align with operational scale and management objectives.

Objectives

In this paper, we review the range of approaches used to characterize CaBH, describing their conceptual foundations, data requirements, and potential sources of disagreement. Building on this methodological foundation, we conduct a case study across 93 field sites in northern New Mexico (USA) to evaluate how measurement approach shapes CaBH characterization and alters modeled crown fire hazard. Although geographically focused,

our study area spans a wide variety of forest types, fire regimes, and management priorities (New Mexico Forest Action Plan 2020) making the methods and implications broadly relevant to forest managers, modelers, and policymakers across fire-prone, conifer landscapes. Our objectives in this case study were to (1) assess differences in CaBH across data sources and analytical methods, (2) quantify how these differences vary across forest types, (3) evaluate the implications of these CaBH differences for modeled crown fire initiation under site-specific conditions and a standardized moisture scenario, and (4) evaluate the relationship between within-plot variability in tree height and among-method variability in CaBH across forest types. We expected greater divergence in CaBH among approaches in plots with higher heterogeneity in tree height, due to their higher within-stand variation in tree CrBH.

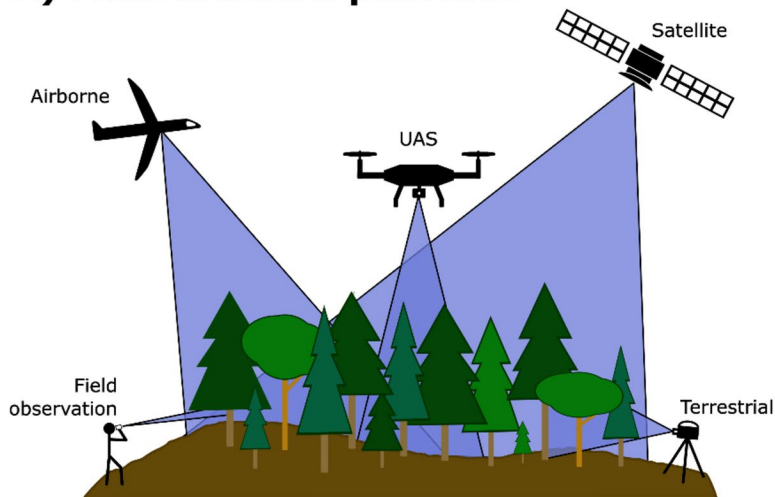
Review of CaBH characterization approaches

In the following section, we describe approaches to characterize CaBH directly using field-measured and Lidar-extracted CrBH and indirectly using plot-level allometry and satellite-based models. These approaches span a range of data types (e.g., field measurement, point clouds, Lidar waveforms, and imagery), platforms (terrestrial, UAS, airborne, and satellite), and conceptual definitions (CrBH aggregation and fuel density thresholds) across spatial extents from plot-level to national scales (Fig. 1). While not exhaustive, the following sections reflect common approaches used in research and management. For clarity, the approaches are grouped by primary data type: field observation, point cloud (Lidar and structure from motion), and satellite imagery.

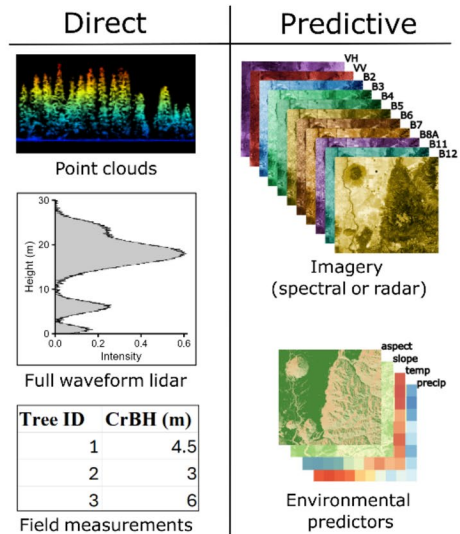
Field-based methods

Canopy base height (CaBH) can be derived by aggregating a set of field-measured crown base heights (CrBH), the height above ground of the lowest live branch that belongs to an individual tree crown, quantified using thresholds for branch thickness and vertical continuity (Schomaker 2007). Crown base height is measured using standard height-measuring instruments (e.g., clinometer, laser rangefinder, or height pole), accounting for tree lean (Waskiewicz et al. 2015). It is common for field crews to only measure CrBH for trees exceeding a diameter-at-breast-height (DBH) threshold or belonging to specific crown classes (e.g., dominant or co-dominant trees). Once all relevant trees are measured, CaBH can be derived from these individual CrBH values using summary statistics. It is important to note that field-measured forest attributes should not be treated as having absolute accuracy because they are subject to inherent errors and bias from factors such as incorrect instrument

A) Measurement platform



B) Data type



C) Conceptual definition

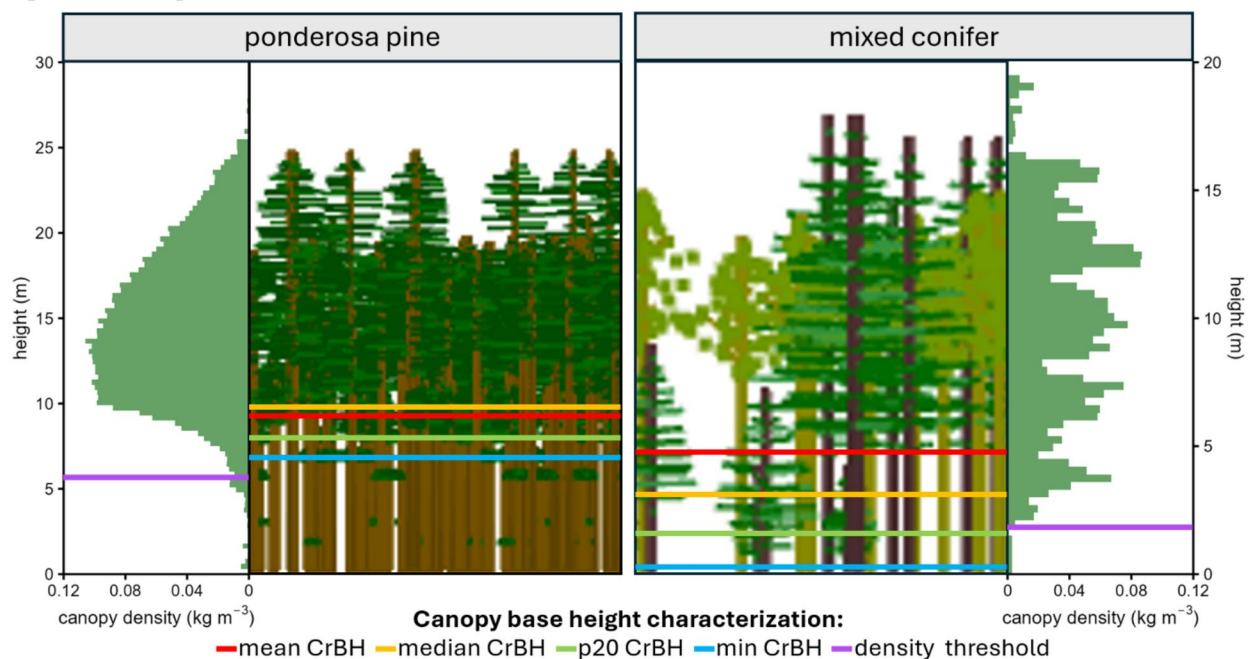


Fig. 1 Overview of approaches to characterizing canopy base height (CaBH). **A** Platforms for measuring structure, including field observation, terrestrial, uncrewed aerial systems (UAS), airborne, and satellite remote sensing. **B** Data types used to directly estimate CaBH (point clouds, full waveform Lidar, and field measurements) and predict CaBH through modeling (spectral or radar imagery and environmental predictors) **C** Different conceptual definitions for characterizing CaBH, including aggregated crown base heights (CrBH) and a canopy fuel density threshold. Definitions diverge in forests with high tree height variability as illustrated here by comparing an even-aged ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson) site and an uneven-aged mixed conifer site. CaBH lines represent four CrBH aggregations (mean, median, 20th percentile, and minimum) and a canopy density threshold, all derived from FVS-FFE simulations of field-measured stands. Full waveform Lidar and canopy density profiles produced for illustrative purposes using hypothetical data

calibration, crew experience, and improper measurement protocol (Westfall and Woodall 2007; Wang et al. 2019).

Common aggregation methods used to represent CaBH include the mean, median, minimum, and lower

quantiles (e.g., 20th percentile) of CrBH. Notably, the empirical relationships in Van Wagner (1977) were derived using mean CrBH, which has contributed to its widespread use in fire behavior models. However, the

experiments used to derive these relationships were predominantly conducted in even-aged stands of a single pine species, which may not accurately reflect conditions across other forest systems. In uneven-aged stands, the use of mean CrBH may obscure the importance of trees with low CrBH in propagating fire into the canopy. To overcome the perceived underestimation of lower canopy structural importance in uneven-aged forests, many studies use lower-tail aggregations of CrBH such as the 20th percentile or first quartile (Fulé et al. 2001, 2002; Skinner 2005; Hunter et al. 2011; Pierce et al. 2012). For conservative planning, managers may choose the minimum crown base height to reflect the possibility that surface fire can reach the canopy at any point within a stand (Graham et al. 1999; Lutes et al. 2006; Prichard et al. 2013; Jaffe et al. 2023). In contrast, for fire-behavior analyses in even-aged forests or wildlife habitat models (e.g., for raptors), managers may prefer to use mean CrBH as a measure of CaBH to better align with the original model development or to describe the overall vertical structure relevant to wind sheltering, visibility, and movement (Bruggeman et al. 2014; Dickson et al. 2014). In even-aged stands with relatively uniform vertical structure, these CrBH aggregations are expected to converge. However, in uneven-aged stands, characterization may vary widely depending on the aggregation method, making it essential to align the method with the management or research goal (Fig. 1C).

Another common approach for estimating CaBH from field data relies on allometric equations which predict CaBH from more easily measured stand attributes without direct CrBH measurement. For example, Cruz et al. (2003) developed equations for predicting CaBH using basal area and stand height which explained between 64 and 88% of the variation in CaBH depending on the forest type. Allometric equations can also be used indirectly to estimate CaBH. For example, the Forest Vegetation Simulator Fire and Fuels Extension (FVS-FFE) predicts CaBH by simulating the vertical arrangement of canopy fuels using species- and region-specific allometries applied to user-provided tree inventory data, such as species, DBH, and tree height (Reinhardt and Crookston 2003; Crookston and Dixon 2005). FVS-FFE predicts all foliar biomass and a portion of fine twig (<0.635 cm diameter) biomass from field inventory data and distributes it to 0.3 m tall vertical canopy bulk density bins. Canopy base height is then defined as the lowest height at which canopy bulk density exceeds a fixed threshold of 0.011 kg/m³ for a running average across three of the 0.3 m slices (Scott and Reinhardt 2001; Andersen et al. 2005). Importantly, CaBH in FVS-FFE represents the minimum fuel density required to support horizontal fire spread within the canopy rather than the vertical spread, constituting a

change from the original canopy base height definition proposed by Van Wagner (1977).

While FVS-FFE is a dynamic model, it can also be applied statically to simulate fuel conditions at a single timestep. FVS-FFE uses crown ratios, the proportion of total tree height occupied by the live crown, to refine biomass profiles. This variable is directly linked to CrBH and can be provided by the user. However, when crown ratios are not provided, FVS employs variant-specific (i.e., geographically calibrated) models to estimate individual crown ratios from tree- and stand-level attributes, such as DBH, tree height, and total basal area in trees above the diameter class of the subject tree (FVS Staff 2008). While effective for regional applications, the model's reliance on generalized allometries may limit sensitivity to fine-scale variation, smoothing over spatial heterogeneity.

Point cloud-based methods (lidar and SfM photogrammetry)

Point clouds are discrete sets of 3D coordinates typically produced using Lidar or photogrammetric techniques. Lidar sensors measure forest structure by emitting laser pulses and recording time-of-flight to surfaces, such as canopy foliage, branches, or the ground, to generate point cloud data that provides detailed three-dimensional information on forest structure (Lefsky et al. 2002; Wulder et al. 2012). Lidar sensors can be deployed terrestrially, from UAS, planes, and satellites. Supported by a vast body of research, the adoption of Lidar to generate or supplement forest inventory data has expanded significantly due to the growing availability of data and advancements in laser scanning technology (White et al. 2016; Fassnacht et al. 2024). Lidar is particularly valuable for mapping vertical forest structure, as some laser pulses penetrate through canopy gaps to reach lower vegetation and the forest floor, allowing users to create detailed vegetation height profiles. High agreement has been found between field- and Lidar-measured CaBH, in both managed and unmanaged forests (Andersen et al. 2005; Chamberlain et al. 2021).

Lidar can be operationalized on a variety of platforms, including handheld terrestrial laser scanning (TLS), uncrewed aerial systems (UAS), fixed wing crewed aircraft, and satellites (i.e., spaceborne sensors). The most suitable platform depends on the required level of detail and accuracy (e.g., point density and location error), the spatial extent needed to be covered, and which vegetation layers are of most interest to the user (Atkins et al. 2023). TLS and UAS yield the densest point clouds but cover the smallest areas. TLS, which is deployed at ground point locations, can provide an accurate view of vegetation and fuels under the canopy, while UAS flights above the canopy can provide an accurate view of the top of the canopy

while covering a broader, continuous extent. Airborne Lidar captured from fixed wing crewed aircraft typically has a lower point density than can be achieved with UAS (tens vs. thousands of points m^{-2}) but allows users to map forest structure over millions of hectares compared to the smaller mission extents typical of UAS. Satellite Lidar systems provide broad-scale measurements of forest structure and include full-waveform systems such as the Global Ecosystem Dynamics Investigation (GEDI) and photon-counting systems such as the Ice, Cloud, and land Elevation Satellite 2 (ICESat-2). These systems can be used to characterize the vertical distribution of fuels (Hakkenberg et al. 2024) but are limited by vertical signal mixing and large spatial footprints (e.g., 25 m for GEDI), making detection of lower canopy structure difficult. Therefore, Lidar collected from satellites is better suited to broad-scale characterization of vegetation height and as a predictor in models trained with higher resolution data (Saatchi and Favrichon 2023; Aragonese et al. 2024).

A common approach to characterizing CaBH from discrete return Lidar is to analyze the vertical point density profile for a designated area, whether a stand, gridded data cell, or individual tree crown. At the tree level, this is accomplished by first segmenting individual tree crowns from the point cloud using two distinct methods (Koch et al. 2014; Sparks et al. 2022). The first method segments trees directly from the point cloud data by clustering points based on expected tree crown shape and spacing (Li et al. 2012; Dalponte and Coomes 2016; Silva et al. 2016). The second method utilizes the point cloud to generate a canopy height model (CHM) raster from which local maxima (i.e., treetops) are identified, crown boundaries are delineated based on expected crown dimensions, and point cloud data are cropped to crown boundaries (Hyypä et al. 2001; Popescu and Wynne 2004). While these traditional tree detection methods require that parameters be tailored to the dominant vegetation due to crown structural differences among species, deep learning methods that do not require such parameter tuning are advancing (Wielgosz et al. 2024; Xiang et al. 2024), though their operational use remains limited.

In tree-centric workflows, the vertical distribution of points in the point cloud is then assessed to identify fuel layers based on point density. A variety of criteria exist for selecting the fuel layer which constitutes the lowest canopy layer, including the fuel layer with maximum point density, minimum distance from the ground, and the last layer with effective distance between it and the next lowest layer (inhibiting vertical fire spread; Viedma et al. 2024). When calculated at the tree level, this provides estimates of CrBH, which can be aggregated using any of the aggregation methods described in the previous

section or used along with other forest structure variables in FVS-FFE to produce estimates of CaBH.

While this tree-centric approach is common when characterizing canopy fuels using point cloud data, especially when other tree-level attributes are of interest, CaBH can also be characterized directly from the vertical distribution of points at scales coarser than individual crowns, bypassing tree delineation. This approach treats CaBH as a plot-level or continuous forest attribute. Methods for plot-level CaBH estimation include voxel-based point density profiles, height percentiles, and gap fractions (Riaño et al. 2003; Andersen et al. 2005; Maguya et al. 2015). This coarse-grain approach can be advantageous when tree delineation is unreliable due to dense, structurally complex forest conditions or sparse point clouds (Stefanidou et al. 2020).

Another approach to generating point clouds is structure-from-motion (SfM) photogrammetry, which produces point clouds analogous to Lidar using a sequence of overlapping images and is a common data acquisition technique in UAS and plane-based remote sensing (Goodbody et al. 2019; Iglhaut et al. 2019). While the camera-based sensors used in SfM photogrammetry are considerably cheaper than Lidar systems, enabling inexpensive forest inventories, their passive nature limits canopy penetration and can reduce performance in tall, structurally complex forests due to shading. This makes the measurement of subcanopy and bottom-of-canopy vegetation challenging, especially in dense forest conditions (Kelly et al. 2025). Despite this challenge, SfM photogrammetry has been successfully employed to estimate forest structure (Lamping et al. 2021; Strunk et al. 2022), especially in open forest conditions, and has, in some cases, yielded measurements of CaBH that are comparable with airborne Lidar measurements (Filippelli et al. 2019; Creasy et al. 2021; Batchelor et al. 2025).

Satellite-based methods

Spatially exhaustive and timely fuel maps are required for landscape- to regional-scale fire modeling and rapid response simulations. Although field- and Lidar-based methods can provide high-accuracy estimates of fuel conditions, these data are rarely available over broad (landscape to continental) extents, are often temporally outdated, and are costly to collect. Satellite-based methods provide a means to address these spatial constraints. While direct measurement of CaBH from spaceborne sensors has not been implemented, satellite platforms still serve an important role in broad-extent canopy fuel mapping, through both active (e.g., Lidar and radar) and passive (e.g., multispectral) sensors. Spaceborne Lidar can produce vertical vegetation profiles but is limited by relatively coarse-grain sensor footprints and track

spacing that prevents wall-to-wall coverage. Spaceborne radar operates at longer wavelengths than Lidar and cannot directly measure canopy fuel strata. However, it is sensitive to canopy structure, providing useful information on vegetation density and vertical complexity. Passive satellite sensors also struggle to map vertical structure due to a top-of-canopy view that obscures the understory (Turner et al. 1999; Lu 2006). Therefore, data collected from satellites are often paired with high-fidelity field- or Lidar-derived measurements to model fuel conditions across large areas.

This approach to broad-scale mapping is the concept behind the widely used LANDFIRE fuel products, which provide a suite of maps for the USA relevant to fire behavior modeling and forest management (La Puma 2023). Created as part of the 2000 National Fire Plan, LANDFIRE is an interagency data program that uses a combination of Landsat imagery, forest inventory data, Lidar, and disturbance effects models to produce annual maps of fuels and vegetation across the USA and its territories. New Landsat imagery was incorporated as part of the 2001 and 2016 LANDFIRE products and CaBH was modeled using Cubist regression trees, with predictor variables including canopy height, canopy cover, existing vegetation type, Landsat spectral data, and recent disturbance history (Rollins 2009). Since LANDFIRE CaBH maps were produced using models trained on field measurements input into FVS-FFE, it defines CaBH as the lowest point where there is enough available fuel (>0.25 inches in diameter) to propagate the horizontal spread of fire through the canopy. For LANDFIRE estimates of CaBH in years other than 2001 or 2016, CaBH values in undisturbed areas are carried forward from the last remap, while CaBH in disturbed areas is recalculated using linear equations derived from FVS. In this way, LANDFIRE represents a hybrid approach to mapping fuel structure that combines satellite-based vegetation structure with statistical and machine-learning models informed by extensive field data and expert input. Although LANDFIRE products effectively capture regional and national patterns in CaBH, lower accuracy at fine spatial scales may underrepresent local fuel heterogeneity (Pierce et al. 2012), requiring adjustment of estimates for use in fire behavior modeling. For instance, Krasnow et al. (2009) found that LANDFIRE overpredicted field-measured CaBH by an average of 0.7 m, leading to underpredictions of fire spread. This lack of local accuracy may be a result of the moderate (30 m × 30 m) resolution of Landsat and the lack of continuous structural predictor data (Engelstad et al. 2019).

The fusion of Lidar with satellite imagery to improve forest attribute mapping has become increasingly common over the past decade (Balestra et al. 2024). In this

approach, satellite-based models are trained directly using high-resolution airborne Lidar or TLS to produce wall-to-wall maps of forest structure that often achieve higher accuracy than possible with either individual data source and cover extents exceeding most Lidar data acquisitions (Ahmed et al. 2015; Zald et al. 2016; Bright et al. 2017; Domingo et al. 2020). Furthermore, fusion approaches can reduce overreliance on surrogate relationships with vegetation types or expert-derived rules. Passive satellite sensors can also be paired with active sensors to account for both the spectral signature and the roughness of the Earth's surface (California Forest Observatory, 2020; Vallet L, Mast CN, Banerjee S, Zald H, Hurtleau MD, Jones GM, Francis EJ: In review. 4D-FUELS: A LiDAR-to-satellite system for mapping and monitoring forest structure and fuels, in review). This data fusion approach is further detailed in the case study below.

Case study methods

The review of CaBH quantification methods in the preceding section suggests that characterizations differ systematically across data sources and analytical approaches, with likely consequences for predicted fire behavior. This case study tests these implications in northern New Mexico by (1) quantifying how CaBH varies across approaches and forest types; (2) assessing how this variability translates to differences in modeled torching index; and (3) relating among-method variability in CaBH and torching index to within-plot tree height variability.

Study area

Our study area spans 4.16 million hectares of northern New Mexico and contains 3.75 million hectares of forest, encompassing the entirety of the Santa Fe and Carson National Forests and portions of the Cibola, Rio Grande, and San Juan National Forests (Fig. 2). Based on small-area estimation of woodland ownership (Harris et al. 2021), most forested area in our study area is federally owned (57%), followed by corporate (18%), family (14%), tribal (6%), and state (4%) ownership. Elevation ranges from 1500 to 4000 m, creating diverse climates, vegetation assemblages, and fire regimes (Vankat 2013). The dominant forest types, based on the USFS *Forest Type Groups 2018 (BIGMAP)* product, are pinyon-juniper (45% of forest area), mixed conifer (22%), ponderosa pine (14%), spruce-fir (9%), and aspen (6%) (USDA Forest Service, Forest Inventory and Analysis Program 2021). This diversity of forest types and fire regimes makes the region well-suited for comparing CaBH characterization methods over a spectrum of forest conditions, from open, even-aged canopies to dense, closed canopies with high vertical variability and infilling. Below, we describe the typical elevations, climatic conditions, species compositions, and

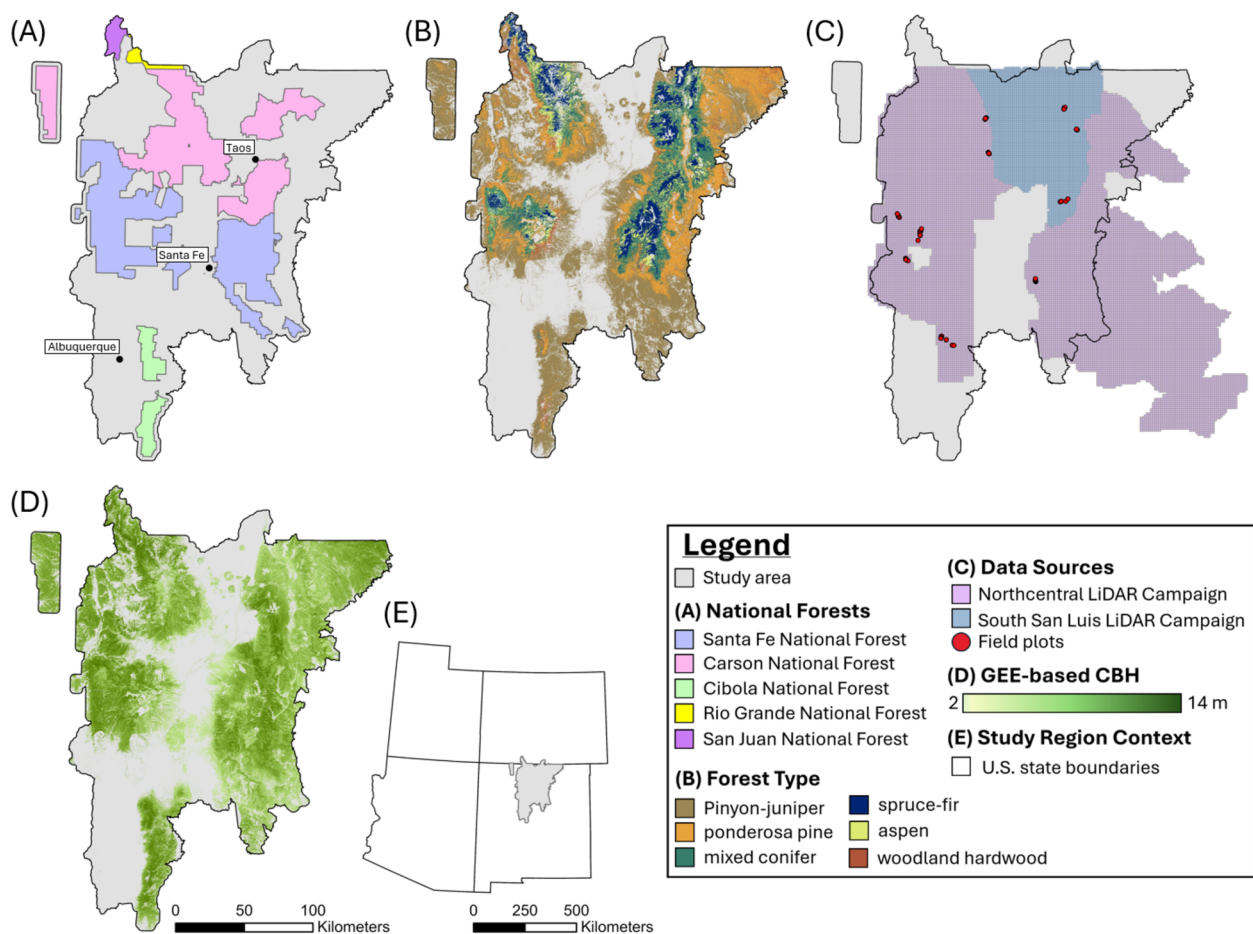


Fig. 2 Map of our study area in northern New Mexico and southern Colorado displaying **A** national forest boundaries, **B** dominant forest types based on USFS BIGMAP forest type groups, **C** dataset coverage showing 2016–2017 Lidar campaign tiles and 2023 field plots, **D** wall-to-wall 2017 canopy base height from a satellite-based random forest model in Google Earth Engine (GEE) masked to forested area and shown for context, and **E** study area location in the four-corners region of the USA

fire regimes within the four dominant conifer forest types of our study area. We summarize conditions using the USFS FIA plot network, LANDFIRE's 2020 elevation product, and TopoTerra's downscaled 1961–1990 maximum July temperature and annual climatic water deficit products (LANDFIRE 2020a, b; USDA Forest Service, Forest Inventory and Analysis Program 2022; Hoecker et al. 2025). Because BIGMAP is a classified map product derived from remote sensing, it may contain misclassified pixels that place forest types outside their true environmental ranges. Therefore, we report elevation and climatic conditions using the 10th and 90th percentiles to reduce the influence of potential outliers and describe the conditions under which forest types typically occur.

Pinyon-juniper woodlands are the largest forest type in our study area by extent. Typically growing at lower elevations between 2000 and 2400 m, pinyon-juniper woodlands have the highest maximum July temperatures (26 to 30 °C) and annual climatic water deficits (600 to

1050 mm). The dominant species by basal area are one-seed juniper (*Juniperus monosperma* (Engelm.) Sarg.), two-needle pinyon (*Pinus edulis* Engelm.), and Rocky Mountain juniper (*Juniperus scopulorum* Sarg.). Dendrochronology research suggests that pinyon-juniper woodlands historically experienced primarily patchy, infrequent, stand replacing fires, with fire spread often limited by fuel discontinuity (Huffman et al. 2008; Shinneman and Baker 2009).

Ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson) forests typically occur between 2250 and 2700 m in elevation and have lower maximum July temperatures, ranging from 24 to 27 °C, and annual climatic water deficits ranging from 450 to 800 mm. Common species occurring alongside ponderosa pine include Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) and white fir (*Abies concolor* (Gord. & Glend.) Lindl. ex Hildebr.). Fire-resistant traits, such as thick bark, self-pruning, and deep roots, along with open forest structure and dry understory

microclimates historically promoted frequent, predominantly low-severity fires (Harrington 1982; Covington 2003).

Occurring between 2550 and 3000 m in elevation, mixed conifer forests, which are classified as the Douglas-fir group in FIA BIGMAP, are comprised predominantly of Douglas-fir, white fir, and quaking aspen (*Populus tremuloides* Michx.). Mixed conifer forests have maximum temperatures ranging from 21 to 25 °C and climatic water deficits between 300 and 550 mm. Fires in southwestern mixed conifer forests were historically shaped by species composition, stand structure, topography, and climate, with both low- and high-severity fires playing a role in landscape dynamics and fire frequency decreasing at higher elevations (Touchan et al. 1996; Wolf and Mast 1998; Brown et al. 2001). At lower elevations and on south-facing slopes, usually characterized by increased ponderosa pine occurrence and an open understory, frequent, low-severity fire makes up a higher proportion of the historical fire regime. However, unlike lower elevation ponderosa pine forests, surface fires in mixed conifer forests are largely moisture-limited as opposed to fuel-limited (Vankat 2013). At the upper end of its elevation range where species composition begins to transition to spruce-fir and on north-facing, mesic sites, fire becomes more climate-limited, shifting towards more infrequent, patchy, and high-severity events (Margolis et al. 2007, 2011).

Spruce-fir forests occur at the highest range of the elevational gradient, between 2900 and 3500 m. As the most mesic forest type in the region, spruce-fir forests have the lowest maximum July temperatures (between 18 and 22 °C) and annual climatic water deficits (150 to 350 mm). Dominant species include Engelmann spruce (*Picea engelmannii* Parry ex Engelm.), white fir, and Douglas-fir. Fire in spruce-fir forests was historically limited by snow-pack driven fuel moisture, with infrequent, high-severity fire events occurring when climatic conditions aligned with fire spread (Abolt 1997; Margolis et al. 2011).

CaBH characterization

To assess how CaBH quantification varies by method and forest type, we first calculated field-based metrics of CaBH for 121 fixed-radius plots (11.3 m radius) across three national forests in northern New Mexico using data collected in 2023. Each circular plot was 400 m² and located in forest stands on national forest lands. Plot locations were selected to cover the major forest types present in the region based on elevation ranges, with each site located at least 20 m from roads and other plots. Areas with evidence of recent management or disturbance based on visual assessment were avoided to minimize disturbance-driven disagreement with the

2016 and 2017 Lidar data acquisitions (described below). Plots were then screened against fire perimeters from the Monitoring Trends in Burn Severity dataset and active forest management perimeters from the Forest Activity Tracking System to remove recently disturbed plots (Eidenshink et al. 2007; USDA Forest Service 2024). Finally, plots without GPS or species data were removed resulting in a final data set consisting of 93 undisturbed field plots. The location of each plot center was measured using an EMLID RS3 GNSS receiver (Emlid Ltd., Budapest, Hungary) employed with stop-and-go kinematic surveying, with data post-processed in Emlid Studio using CORS stations to achieve sub-meter accuracy (Valente et al. 2020). Within each plot, all live trees ≥ 5 cm DBH were measured for species, DBH, total height, and CrBH. CrBH was measured to the nearest 0.3 m using a laser rangefinder or clinometer. Following FIA protocol, branches with live vegetation greater than 2.5 cm in diameter were included as part of the crown if they were within 1.5 m of the next live branch. All height measurements were made three times to improve accuracy and were averaged before analysis. For species with multiple stems, such as oneseed juniper, the diameters of the four largest stems were measured and the largest selected as diameter for FVS modeling. CrBH of trees with multiple stems was measured as the lowest live canopy vegetation on the tree, regardless of which stem it was attached to. Forest structure varied across sites, with conditions ranging from sparse, open canopy ponderosa pine to dense, closed canopy spruce-fir.

Field-based CaBH characterizations were derived for each field plot, including the mean, median, 20th percentile, and minimum of individual tree CrBH measurements (see [Field-based methods](#) section). Field data were also input into the USFS Forest Vegetation Simulator's Fire and Fuels Extension (FVS-FFE) using the Central Rockies variant to generate CaBH estimates based on predicted vertical distributions of canopy bulk density (FVS Staff 2008). These estimates were generated both with and without the inclusion of field-measured crown ratios, which were calculated as unadjusted crown ratios using measured tree height and CrBH. This was done to test FVS's internal logic for estimating crown ratios, which are calculated for each tree using species-specific coefficients based on tree height, diameter, and the basal area of larger trees, and are subsequently used to vertically distribute crown biomass.

Lidar measurements were generated from two airborne Lidar acquisitions flown in the fall of 2016 and spring of 2017, obtained from publicly available USGS 3DEP data (<https://apps.nationalmap.gov/downloader/>). Together, these two campaigns cover 3.98 million hectares, with 2.8 million hectares overlapping our study area. A Leica ALS80

HP 1000 kHz Multiple Pulses in Air (MPiA) Lidar system was used to collect the data at a nominal pulse spacing of 0.70 m and a resulting point cloud density of 6.0 points/m². Raw point cloud data were processed in R using functions from the *lidR* (Roussel et al. 2020), *lasR* (Roussel 2025), *ForestTools* (Plowright and Roussel 2025), and *LadderFuelsR* (Viedma et al. 2024) packages as integrated in the *cloud2trees* package (Woolsey 2026). A 0.25-m resolution canopy height model was generated by classifying raw points as ground or non-ground, removing outlier points, triangulating the ground points into a digital terrain model, height-normalizing the point cloud, and rasterizing the normalized point cloud by assigning the maximum point height to each output pixel. Individual tree locations were detected from the canopy height model using the local maxima filtering algorithm in *LidR* (Popescu and Wynne 2004) and crowns were segmented using the marker-controlled watershed method in *ForestTools* (Plowright and Roussel 2025).

Because the point density within many tree crowns was insufficient for direct CrBH estimation, CrBH was calculated from the point cloud for only a subset of trees (14%) using the maximum leaf area density (LAD), maximum distance, and last distance algorithms implemented in the *LadderFuelsR* package (Viedma et al. 2023, 2024). For trees lacking sufficient data for direct measurement, the *cloud2trees* package predicted CrBH using local height-to-CrBH relationships derived from trees where CrBH was successfully extracted from the point cloud. To avoid unrealistically low CrBH values associated with dense near-ground returns arising from misclassified ground returns (Fig. S1), a minimum CrBH of 0.5 m was enforced for all algorithms. For each plot, CrBH was aggregated using the same summary statistics applied to the field data (mean, median, 20th percentile, and minimum) to calculate CaBH. Because results among fuel layer selection algorithms in the *LadderFuelsR* package were similar (mean difference of 3.4 cm across 87,500 directly measured trees), reflecting consistent selection of the same fuel layer, only the last distance algorithm was retained for cross-method comparison. This algorithm defines the CrBH based on the lowest vertical distance between fuel layers, where a layer is defined as a vertical cluster of points meeting a minimum density threshold.

Satellite-derived CaBH estimates were obtained from the LANDFIRE 2023 CaBH product (2023a) and from a Sentinel-based random forest model trained on the 2016–2017 Lidar maps developed for this study. The random forest model was trained in Google Earth Engine (GEE) to enable efficient acquisition, preprocessing, and integration of satellite data (Gorelick et al. 2017). Sentinel-2 spectral bands were filtered to remove clouds and cirrus using QA60 bitmasks and a cloud-probability

threshold (>40%), and median composites were generated for the summer season (June–September). Seasonal composites of Sentinel-1 VV and VH backscatter and their VV/VH ratio were also generated. Bands were resampled using a bilinear algorithm to a 10-m resolution, yielding a final predictor stack consisting of all Sentinel-2 bands together with Sentinel-1 VV, VH, and VV/VH. The model was trained using 100,000 point samples of Lidar-derived forest structure metrics generated from the same 2016–2017 Lidar acquisitions described above. Point samples were randomly selected from forested areas, and model outputs were masked to forest areas using annual masks derived from the National Land Cover Database (NLCD) tree canopy cover product using a 10% canopy cover threshold (Housman et al. 2026). The model output corresponds to the mean prediction of two random forest models (50 trees each) and produces annual, spatially continuous maps of forest structure from 2015 to 2025 across the full 4.16-million-hectare study area. Plot-level CaBH was then calculated using a weighted average of the 2023 random forest prediction on each plot footprint.

Fire behavior model parameterization

To assess how choice of CaBH method influences predicted crown fire initiation across northern New Mexican forests, torching index was modeled for each plot and CaBH characterization approach using the *firebehaviorR* package (Ziegler et al. 2019). To parameterize site conditions, input data were obtained from a variety of sources. We assigned Scott and Burgan fuel models to each plot using LANDFIRE's 2023 FBFM40 product (2023b), which predicts surface fuel models using a combination of existing vegetation type, cover, height, and biophysical setting (Scott and Burgan 2005; Reeves et al. 2009; Rollins 2009). When multiple fuel models were present within the same plot, the dominant model (by spatial extent) was selected (Fig. 3). Wind adjustment factor was calculated using the “waf” function in *firebehaviorR*, which depends on surface fuel depth, canopy height, crown ratio, and canopy cover (Ziegler et al. 2019). Surface fuel depth came from the selected surface fuel model. Canopy height was calculated from the Lidar-derived 10-m canopy height model, and crown ratio as canopy height minus CaBH divided by canopy height, allowing the wind adjustment factor to change with CaBH characterization approach. Finally, canopy cover was derived from the National Land Cover Database's tree canopy cover product, which was selected due to its use of annually updated satellite imagery (MRLC 2025). Slope, which modifies surface rate of spread, was obtained from LANDFIRE's topography products. A “D1L1” fuel moisture scenario was selected to represent extreme drought conditions with very dry dead fuel moisture and fully cured herbaceous fuels, and

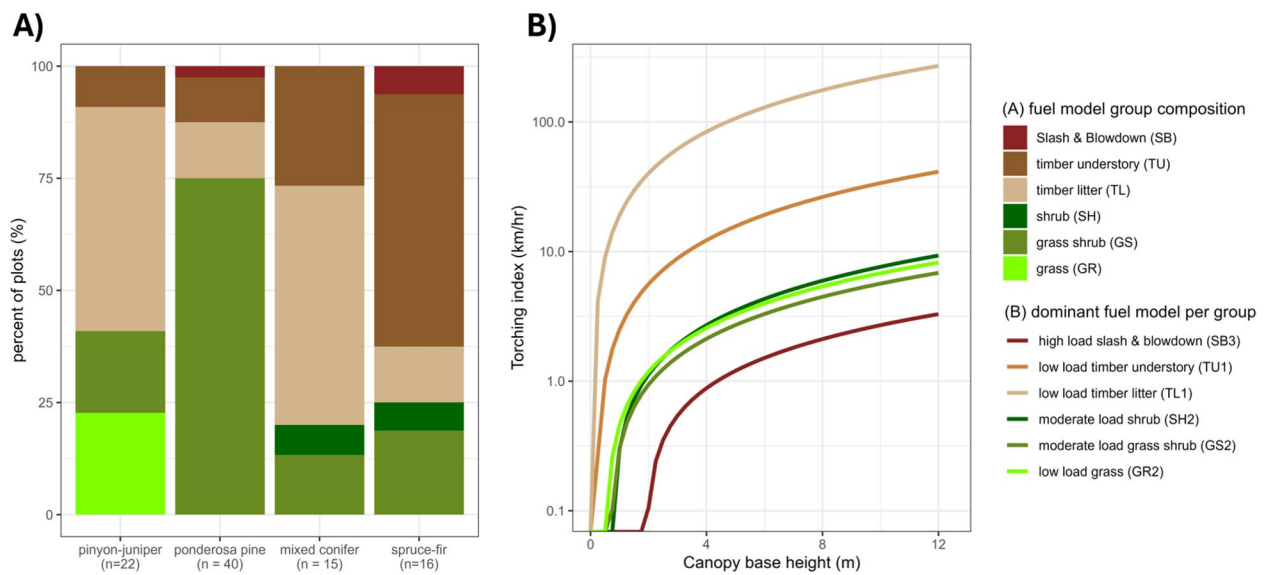


Fig. 3 **A** Proportion of our study plots within each Scott and Burgan fuel model group by forest type, as predicted from the 2023 LANDFIRE FBFM40 product. Our pinyon-juniper sites were dominated by timber litter, ponderosa pine by grass and shrubs, mixed conifer by timber litter, and spruce-fir by timber understory. **B** CaBH-torching index relationships for the dominant Scott and Burgan fuel model within each fuel model group modeled across a continuous range of CaBH values while holding all other variables constant at their mean values across study plots. Note that the y-axis is in $\log_{10}$ scale and that the low load timber litter model is roughly 100 times more sensitive to a change in CaBH from 0 to 4 m than high load slash and blowdown surface fuel model

foliar moisture was set to 90%, also in line with extreme drought conditions (Van Wagner 1977; Scott and Burgan 2005).

Analysis

To assess how CaBH differs across characterization approaches and forest types, we used rank-based nonparametric tests to compare group distributions. These tests were selected due to the heteroscedasticity and non-normality of residuals found in diagnostic checks. Since multiple methods were applied to the same plots, pairwise comparisons between methods were conducted using Wilcoxon signed-rank tests with Bonferroni correction. Because each plot was assigned a single forest type, differences in CaBH across forest types were assessed using a Kruskal-Wallis test, with post hoc pairwise comparisons conducted using Mann-Whitney U tests with Bonferroni correction. Mean plot-level CaBH was calculated across methods prior to forest type comparisons to avoid the pseudoreplication that would arise from including 15 measures of CaBH for each plot. We then applied the same nonparametric tests to compare torching indices among characterization approaches and forest types. To isolate the effect of CaBH characterization on torching index independent of surface fuel variation, we repeated this comparison across all plots using uniform low, moderate, and high load surface fuel models, with results presented in the supplemental. We used $\alpha=0.05$

(p value ≤ 0.05) as the criteria for statistical significance. p values below 0.001 were reported as $p < 0.001$. Adjusted p values were reported where Bonferroni correction was applied, and unadjusted p values where it was not. Bonferroni-adjusted p values are capped at 1.0. Finally, where multiple pairwise comparisons were tested among methods or forest types, we summarized multiple adjusted p values that were all significant or all nonsignificant by reporting the smallest p value of multiple nonsignificant pairs (e.g., all adjusted $p \geq 0.07$) and the largest p value of multiple significant pairs (e.g., all adjusted $p \leq 0.01$). All analyses were conducted in R using the rstatix package (Kassambara 2025).

We expected uneven-aged stands with high tree height variability to have greater disagreement among CaBH characterization approaches compared to even-aged stands due to a wider distribution of individual CrBH values (Fig. 1C). To test this hypothesis for each forest type, we fit linear regression models between plot-level standard deviation of tree height and among-method standard deviation of CaBH. Residual plots indicated no major violations of linearity or homoscedasticity (residuals vs. fitted) or normality (Q-Q plot). Because there is a positive relationship between CaBH and torching index (Fig. 3B), we also expected the importance of characterization choice on modeled torching index to increase with tree height variability. To test this, we fit equivalent linear regression models under low load compact conifer litter

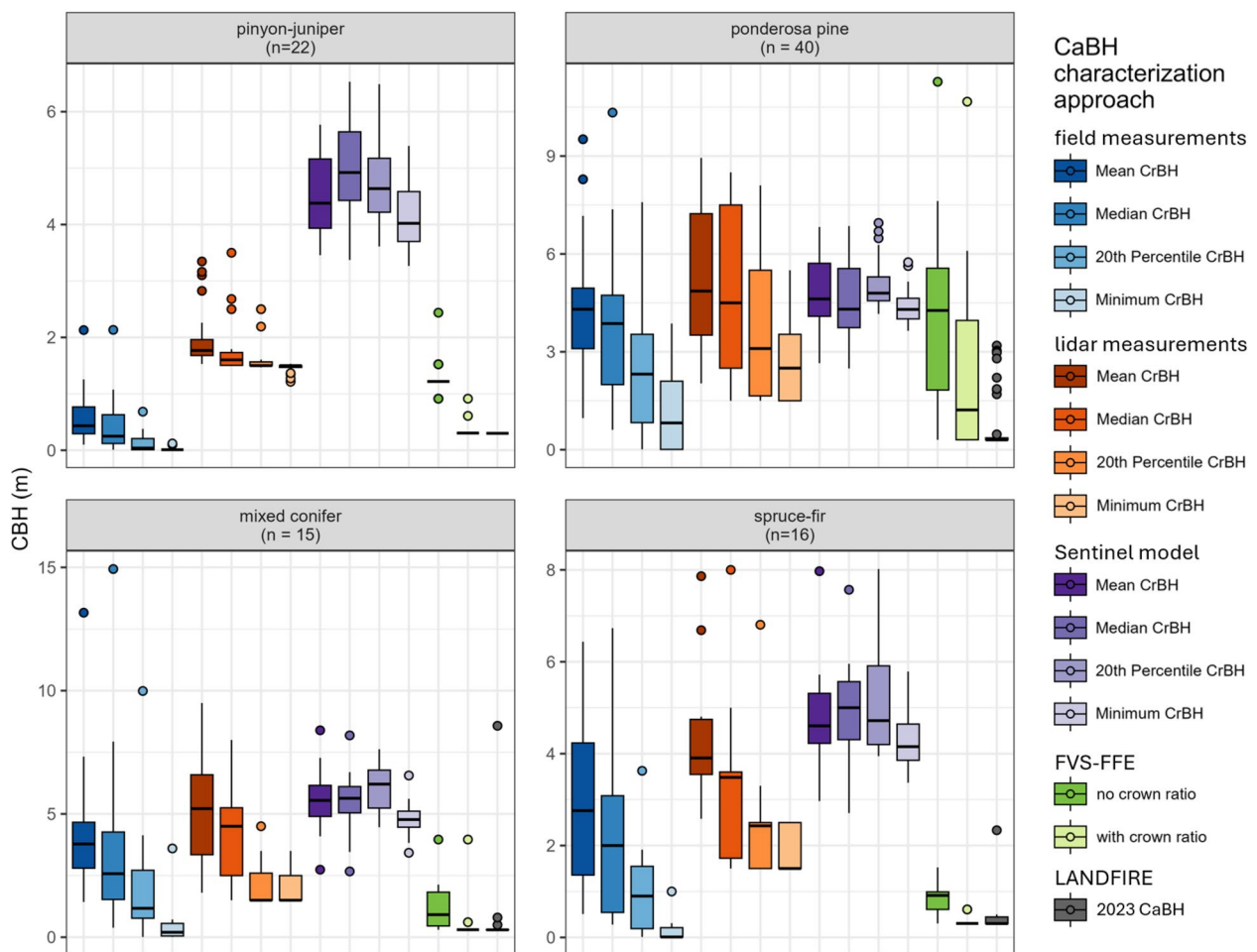


Fig. 4 Boxplot comparison of canopy base height (CaBH) estimates across characterization approaches and forest types in northern New Mexico. CaBH was estimated using direct aggregation of crown base height (CrBH) from field and Lidar measurements, a Sentinel-based model trained on Lidar, a canopy fuel density threshold approach implemented in FVS-FFE using both user-supplied and internally predicted crown ratios, and LANDFIRE. Note that y-axis scale varies, reflecting differences in the range of CaBH values within each forest type

(TL1), moderate load dry climate grass-shrub (GS2), high load activity fuel (SB3), and LANDFIRE predicted Scott and Burgan surface fuel models, with results presented in the supplemental.

Results

CaBH across characterization approaches and forest types

CaBH estimates varied substantially by characterization approach, with a mean within-plot range of 6 m (Fig. 4). The most conservative estimates across all plots were obtained from field-based minimum CrBH (mean = 0.63 m) and LANDFIRE (0.64 m), which did not differ significantly from one another based on Wilcoxon signed-rank tests with Bonferroni correction (adjusted $p = 1.0$). Our four Sentinel-based models produced significantly higher CaBH estimates (4.82 m) than most other approaches (all adjusted $p \leq 0.02$). Exceptions include Lidar-based

mean CrBH (4.33 m), which did not differ significantly from any Sentinel models (all adjusted $p \geq 0.07$), and Lidar-based median CrBH (3.71 m), which did not differ significantly from our Sentinel-based minimum CrBH (4.39 m; adjusted $p = 1.0$). As expected, approaches that aggregated directly measured CrBH (field and Lidar) followed a significant descending pattern across summary statistics (mean > median > 20th percentile > minimum; all adjusted $p < 0.001$). However, Lidar-based CaBH varied significantly from field-based CaBH across summary statistics (adjusted $p < 0.001$ for mean, median, 20th percentile, and minimum), with Lidar estimates averaging 1.07 m higher than field estimates. Disagreement between field- and Lidar-based estimates was similar across summary statistics, with comparable mean absolute error values (mean CrBH = 1.65 m; median CrBH = 1.67 m; 20th percentile CrBH = 1.45 m; minimum CrBH = 1.49

m). Sentinel-based predictions of CaBH did not display the same patterns among summary statistics and were less variable across forest types. This was especially true in pinyon-juniper plots, where satellite-based estimates diverged greatly from other approaches. Modeled CaBH estimates from FVS-FFE that utilized internally predicted crown ratios were significantly higher than those that included observed crown ratios (mean = 2.5 m vs. 1.3 m; adjusted $p < 0.001$). While FVS-FFE predictions based on observed crown ratios were more closely aligned with LANDFIRE predictions than those made using internally predicted crown ratios (mean absolute error = 0.97 m vs. 2.0 m), these approaches still differed significantly (adjusted $p < 0.001$).

CaBH estimates also varied significantly across forest types (Fig. 4; Kruskal-Wallis test: $p < 0.001$). Pairwise Mann-Whitney U tests with Bonferroni correction indicate that pinyon-juniper had significantly lower mean CaBH across methods (1.9 m) compared to the other three forest types (all adjusted $p < 0.001$). Mean CaBH across methods did not differ significantly between ponderosa pine (3.57 m) and mixed conifer (3.26 m) nor between mixed conifer and spruce-fir (2.59 m), though ponderosa pine and spruce-fir were significantly different (adjusted $p = 0.01$). The greatest absolute within-plot variability among approaches occurred in mixed conifer (mean standard deviation = 2.38 m, mean range = 7.11 m), followed by spruce-fir (1.97 m, 5.76 m), ponderosa pine (1.87 m, 6.17 m), and pinyon-juniper (1.84 m, 5.16 m), though only the difference in mean CaBH range between pinyon-juniper and ponderosa pine was significant after Bonferroni correction (adjusted $p = 0.03$). However, as pinyon-juniper plots had substantially lower mean canopy height (6.56 m) compared to the other forest types (22 m), variability relative to canopy height was proportionally higher in pinyon-juniper (CV = 29% vs. 15% across other forest types, Mann-Whitney U test: $p < 0.001$).

Consequences for modeled crown fire hazard

Predicted torching indices varied widely across CaBH characterization methods, with a mean within-plot range of 14 km h⁻¹ (Fig. 5). Patterns in predicted torching index among characterization methods mirrored patterns in CaBH, with the lowest mean torching indices obtained from field-based minimum CrBH (0.3 km h⁻¹) and LANDFIRE (1.1 km h⁻¹). Like CaBH, our four Sentinel-based models produced significantly higher mean torching indices (12 km h⁻¹) than most other approaches (all adjusted $p < 0.03$), except for minimum CrBH from sentinel and mean CrBH from Lidar (adjusted $p = 1.0$). Because torching index increases nonlinearly with CaBH (Fig. 3B), among-method variability was greater

for torching index than CaBH (mean CV: 80% vs. 70%, Wilcoxon signed-rank test: $p < 0.001$). Pairwise Mann-Whitney U tests with Bonferroni correction indicate no significant differences in the mean torching index across forest types under LANDFIRE predicted surface fuel models (all adjusted $p \geq 0.15$). However, differences in mean torching index across forest types under uniform surface fuel models were generally consistent with differences in CaBH, but with no significant difference in mean torching index between ponderosa pine and spruce-fir (adjusted $p = 1.0$; Fig. S2).

Influence of tree height variability on CaBH variability

Variability in CaBH across methods increased with tree height variability for most forest types (Fig. 6). Strong positive relationships were observed in spruce-fir ($R^2 = 0.58$, $p < 0.001$), ponderosa pine ($R^2 = 0.41$, $p < 0.001$), and mixed conifer ($R^2 = 0.31$, $p = 0.03$), with a weaker nonsignificant positive relationship observed in pinyon-juniper ($R^2 = 0.07$, $p = 0.23$). Similar relationships were observed between tree height variability and among-method variability in torching index under constant surface fuel models, but not under varying LANDFIRE predicted fuel models (Fig. S3).

Discussion

Outcomes

Canopy base height (CaBH) is a method-dependent characterization of vertical fuel structure rather than a fixed stand property. Our results show that CaBH characterizations vary significantly across methods and forest types, with variability in CaBH directly translating to differences in predicted torching indices. This methodological sensitivity underscores how measurement decisions can cascade into crown fire hazard predictions relevant to wildfire risk assessment and fuel treatment prioritization. Our results also show that tree height variability can amplify differences among CaBH characterizations and corresponding torching indices.

As expected, CaBH varied systematically by characterization method, with field- and Lidar-based measures of CaBH exhibiting significant sensitivity to the CrBH aggregation method (Fig. 4). Modeling of CaBH using FVS-FFE showed that the mean value can increase by 1 to 2 m if the internal logic is used to estimate crown ratio instead of being user supplied. This is consistent with Tinkham et al. (2017), who found that including crown ratios from field inventoried CrBH on 50 to 70% of trees eliminated the difference in CaBH. Differences between field- and airborne Lidar-based CaBH likely reflect each approach's vantage point and ability to characterize lower canopy fuel structure. Airborne Lidar workflows often struggle to characterize the understory because

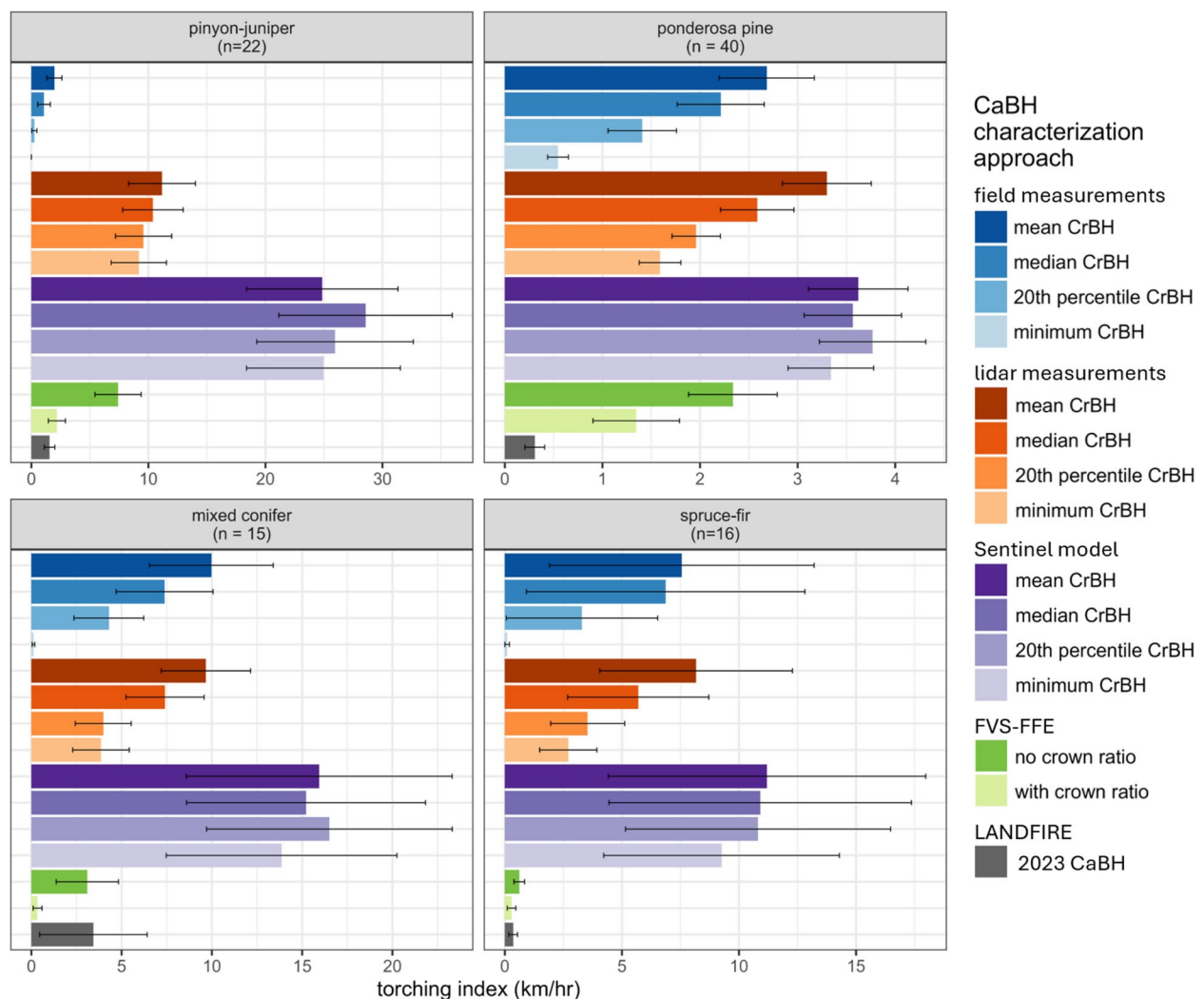


Fig. 5 Predicted torching index (km h^{-1}) based on different canopy base height (CaBH) characterization methods. Bars represent mean torching index with standard error bars. CaBH was estimated directly by aggregating crown base height (CrBH) from field and Lidar measurements and indirectly using a Sentinel-based model trained on Lidar, a canopy fuel density threshold approach implemented in FVS-FFE using both user-supplied and internally predicted crown ratios, and using LANDFIRE's CaBH product derived primarily from Landsat imagery

low branches and smaller trees can be obscured under dense canopy cover, leading to insufficient data density below the upper canopy to capture fine-scale structure. In contrast, field observations made from below the canopy can more easily identify small trees and measure their lower crown structure. Our results reflect this difference, with lower tree densities detected by Lidar relative to field (field tree density = $722 \text{ trees ha}^{-1}$; Lidar tree density = $472 \text{ trees ha}^{-1}$) and Lidar measurements averaging 1.07 m higher than field measurements. These differences also reflect the application of a minimum CrBH of 0.5 m during Lidar CrBH estimation to avoid misclassified ground returns. This constraint disproportionately affected pinyon-juniper plots, where 59.2%

of field-measured CrBH values fell below 0.5 m. In contrast, the other forest types were less affected, with only 15.6% of field-measured values below the threshold. On the other hand, field observations also have limitations for CaBH estimation, as CrBH measurements depend on observer judgment in identifying the base of the live crown and high data collection costs limit spatial coverage. Nonetheless, alignment between field- and Lidar-based measurements was stronger than alignment between the field measurements and our Sentinel-based models. This is consistent with other studies that have found Lidar produces better approximations of field-based CaBH than LANDFIRE (Chamberlain et al. 2021), reinforcing the use of Lidar over satellite models as a

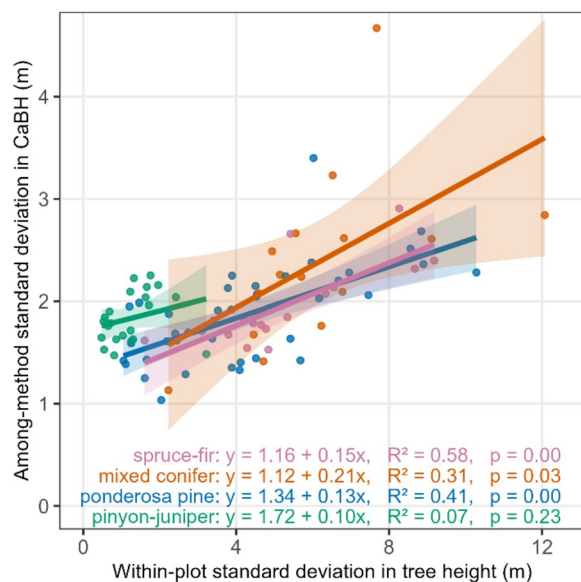


Fig. 6 Among-method variability in CaBH increases with within-plot variability in tree height for most forest types. Each point represents a circular 400 m² plot. Linear models (lines) were fit separately for each forest type (colors), with shaded regions indicating 95% confidence intervals

substitute for field measurement where it is available. CaBH estimates derived from satellite-based multispectral imagery and synthetic aperture radar struggled to capture variability in canopy base height among forest types (Fig. 4, purple boxplots), possibly because of their limitations in measuring below-canopy conditions from their position above the canopy. This may limit their use for both fine- and landscape-scale fire modeling and treatment planning.

While differences in modeled torching index among methods mirrored those observed in CaBH, patterns among forest types did not (Fig. 5). This was likely due to the strong influence of surface fuel model selection, as modeled torching indices among forest types generally followed similar patterns as CaBH when surface fuel model was held constant (Fig. S2). These results demonstrate the importance of both surface fuel model selection and the CaBH characterization approach in shaping modeled crown fire hazard.

We expected stands with greater tree height variability to have greater among-method variability in CaBH and torching index because CrBH aggregation methods differ in their sensitivity to variation in CrBH across trees, and data sources differ in their sensitivity to shorter trees growing under a taller canopy. For an example of the role of CrBH aggregation method, a stand that contains both tall trees with high CrBH and short trees with low CrBH would have different minimum and mean CaBH

values, whereas a stand with trees of a uniform height would have more uniform CrBH values and a smaller difference between the minimum and mean CaBH. Secondly, taller trees can obscure shorter ones from sensors positioned above the canopy, resulting in differences in CaBH estimated from field-based versus remotely sensed observations. In plots where small trees occur below a taller overstory, both mechanisms contribute to among-method disagreement, whereas only differences in CrBH aggregation contribute where multiple patches of varying tree heights occur without vertical overlap. Our expectation was supported in spruce-fir, ponderosa pine, and mixed conifer forests, while a weak, nonsignificant positive relationship was observed in pinyon-juniper. These relationships propagated into torching indices under constant surface fuel models, such that stands with greater tree height variability showed greater variability in torching index across CaBH characterization methods at a constant fuel model (Fig. S3). Our results indicate that heterogeneity in tree height amplifies the importance of CaBH characterization method choice and suggest that managers should exercise greater caution when selecting a characterization approach in areas with forest patches of different tree heights or uneven-aged structure.

Alternative characterization of vertical fuel arrangement

At sufficiently fine spatial scales, CaBH and CrBH become equivalent. Therefore, 3D fuel characterizations that explicitly represent individual tree crowns avoid the methodological differences that arise from how CaBH is characterized. Models such as QUIC-Fire, Fire Dynamics Simulator, and FIRETEC which represent individual tree and crown structure, therefore bypass the need to define CaBH explicitly (Linn et al. 2002, 2020; McGrattan et al. 2013). However, discrepancies stemming from data resolution and detection capability remain, and errors in lower-canopy and near-surface fuel structure detection can still propagate through simulation.

At resolutions coarser than individual crowns, characterizing fuel loading across vertical bins better represents the distribution of fuel within a plot, stand, or pixel and can give managers a more complete depiction of fuel conditions than is possible from individual CrBH statistics (Fig. 7). While this approach can be demanding for rapid assessments and is constrained by the vertical resolution of satellite Lidar, it is readily implemented with airborne or terrestrial Lidar, where high vertical return density supports detailed vertical partitioning. This binning approach has been used to assess forest resilience to wildfire (Steel et al. 2021), model fire severity (Levine et al. 2025), map bird habitat (Davison et al. 2023), and classify vegetation types (Kumar et al. 2018), demonstrating a wide range of applications.

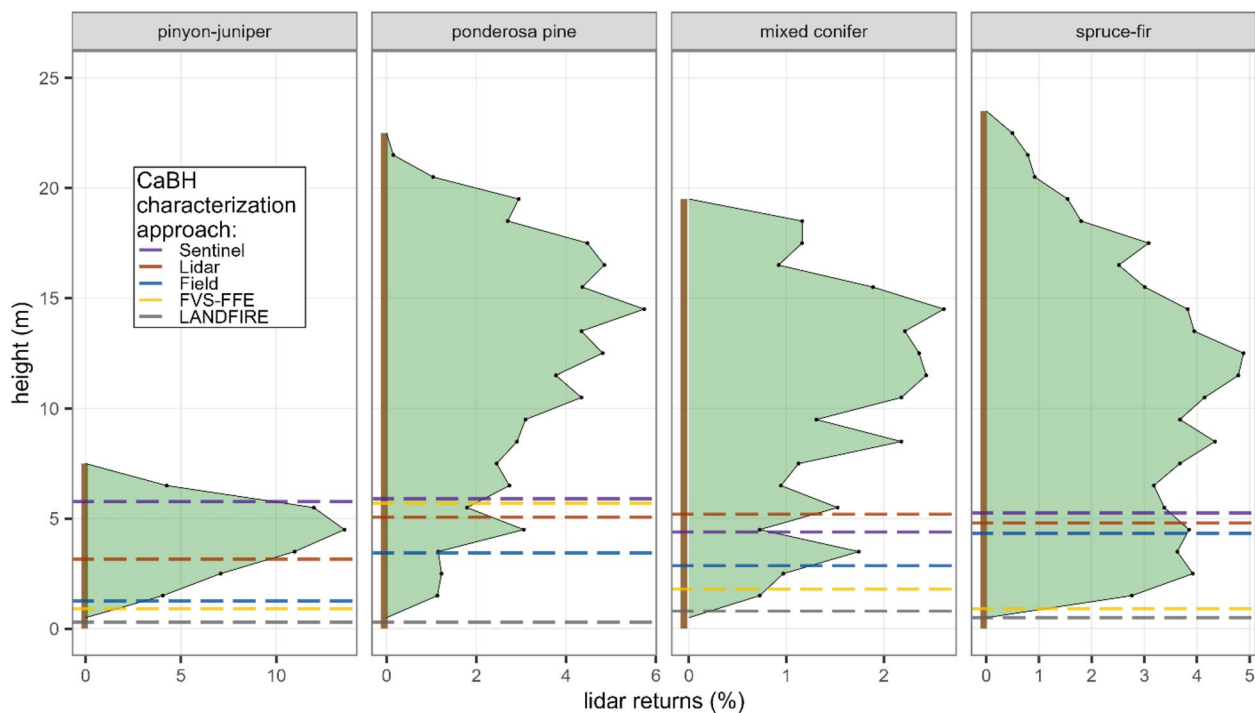


Fig. 7 Vertical percent-Lidar-return profiles (black lines) and select canopy base height approaches (horizontal lines) across four 400 m² plots in major forest types common in northern New Mexico. Plot characteristics vary by forest type: pinyon-juniper (1025 trees ha⁻¹; tree height CV=0.40), ponderosa pine (1200 trees ha⁻¹; tree height CV=0.43), mixed conifer (325 trees ha⁻¹; tree height CV=0.37), and spruce-fir (2175 trees ha⁻¹; tree height CV=0.57). Selected CaBH approaches include mean CrBH from field and Lidar, and modeled CaBH from our Sentinel model (trained on mean CrBH from Lidar), FVS-FFE, and LANDFIRE. Note that the x-axis scale varies by forest type

Limitations

While our comparisons span 93 field plots in northern New Mexico, sampling was restricted to national forest lands and therefore may not represent private timberlands, which make up 18% of forest area in our study area and typically support simpler, even-aged canopies that would likely show lower among-method variability. Furthermore, some degree of spatial mismatch was inevitable: field and Lidar CaBH are linked to trees or crown footprints, whereas LANDFIRE and our satellite-based models provide continuous surfaces at 30- and 10-m resolutions respectively. We applied spatial weighting to reduce misalignment, but within-cell tree positions remain unknown and LANDFIRE and our satellite-based models do not explicitly predict crown or tree locations. There is also a temporal mismatch (Lidar and Sentinel 2017 vs. field and LANDFIRE 2023a, b), and while we removed disturbed plots, growth and age-related mortality may still affect comparisons. Finally, CaBH is method-defined, and we do not argue for or validate any single characterization approach; divergence among methods is expected and should not be interpreted as error.

Implications for forest management

The wide range of torching indices produced across CaBH characterization approaches has important implications for management decisions, including wildfire suppression tactics, the timing of fuel reduction treatments, and the allocation of resources for restoration. During active incidents, where underestimating crown fire potential can have serious safety consequences for wildland firefighters, conservative characterizations of CaBH, such as minimum or lower quantile CrBH, may be most appropriate. In contrast, conservative CaBH values may be overly restrictive for prescribed fire planning, narrowing burn windows and limiting the area that can be safely treated according to fire behavior models designed to use mean CrBH. Therefore, when time and data allow, investigating not only torching index but also crowning index across a range of CaBH characterizations could provide a better understanding of crown fire hazard and which tree sizes are most susceptible to canopy consumption.

For landscape-scale risk modeling and comparative analyses over large extents, satellite-derived CaBH remains a valuable data source due to its spatial

continuity and ability to capture broad patterns in canopy fuels. However, models based purely on satellite imagery are limited at local scales by their inability to accurately represent subcanopy structure and fine-scale variability critical to fire behavior. This is an important limitation, as small differences in CaBH, on the order of 1 m, can substantially alter predicted crown fire potential.

While this study identified conservative and liberal CaBH characterization methods for forests common in northern New Mexico, the method that best predicts actual fire behavior remains uncertain. When modeling forests with even-aged stand structure similar to those used to derive the empirical relationships in Van Wagner (1977), mean CrBH is likely the most appropriate metric because it aligns with the original CaBH defined in the model. However, in forests with multiple canopy layers, the most suitable CaBH characterization method is not well tested. Further research is needed to validate modeled crown fire initiation against observed fire behavior across a range of CaBH characterization approaches and forest conditions to determine which approach best predicts crown fire initiation. Given this uncertainty, treating CaBH as a flexible, context-dependent input that reflects both the scale of decision-making and the structural complexity of the forest being modeled allows managers and modelers to better align CaBH definitions with their respective management and research objectives.

Conclusion

The accurate characterization of forest structure and fuel conditions is essential to informed management, but metrics such as canopy base height (CaBH) are method- and use-case-dependent rather than fixed properties of a stand. Here, we provide a review of different approaches to calculating CaBH, compare them across northern New Mexico forests, and quantify the implications of each approach for predicted fire behavior. Using field data, Lidar, and modeled products, we show that method choice strongly impacts CaBH characterization and that these differences translate into shifts in predicted torching indices under standardized moisture scenarios. Furthermore, results indicate that variability among methods increases with variability in tree height. Therefore, forest planners and analysts must be conscious of how they characterize CaBH and should match their definitions to the decision context. Conservative characterizations (e.g., minimum CrBH or low percentiles) often align more closely with LANDFIRE- and FVS-based operational products and are best suited for risk-averse screening. Conversely, traditional definitions based on mean CrBH may understate ladder fuels in forests with multiple canopy layers. We recommend that practitioners be explicit about the chosen CaBH definition and its

underlying rationale. Where feasible, moving beyond single-metric characterizations of vertical fuel continuity may reduce method-induced ambiguity. Finally, further research is required to validate the ability of different CaBH characterizations to accurately represent observed fire behavior across different forest conditions.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s42408-026-00567-4>.

Supplementary Material 1.

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Authors' contributions

CRedit: CNM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; LV: Data curation, Methodology, Software, Writing – review & editing; MDH: Investigation, Funding acquisition, Writing – review & editing; HSJZ: Investigation, Funding acquisition, Writing – review & editing; GMJ: Funding acquisition, Writing – review & editing; GAW: Software, Writing – review & editing; WTT: Software, Methodology, Writing – review & editing; CHH: Software, Methodology, Writing – review & editing; EJF: Conceptualization, Investigation, Data Curation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

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Data availability

The airborne Lidar data used in this study are publicly available through the U.S. Geological Survey 3D Elevation Program (3DEP), including the NM SC Southern San Luis acquisition and the NM North Central acquisition <https://rockyweb.usgs.gov/vdelivery/Datasets/Staged/Elevation/LPC/Projects/>. Sentinel-1 and Sentinel-2 imagery are publicly accessible via Google Earth Engine. Forest type classifications were based on the USDA Forest Service Forest Type Groups dataset (circa 2018) which can be downloaded at <https://fia-usfs.hub.arcgis.com/>. The code to calculate canopy base height from airborne Lidar and the Google Earth Engine code to calculate canopy base height from Sentinel-1 and Sentinel-2 imagery is available at: <https://github.com/Lilianvall/et/4D-FUELS>. The crown base height field data and analysis code associated with this manuscript will be available at: <https://github.com/ColinMast/CaBH-Methods-and-Implications> upon publication.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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