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Methods in Ecology and Evolution

APPLICATION

LadderFuelsR: A new automated tool for vertical fuel continuity analysis and crown base height detection using light detection and ranging

O. Viedma[1] | C. A. Silva[2] | J. M. Moreno[3] | A. T. Hudak[4]

[1]Department of Environmental Science, University of Castilla-La Mancha (UCLM), Toledo, Spain

[2]Forest Biometrics, Remote Sensing and Artificial Intelligence Laboratory (Silva Lab), School of Forest, Fisheries, and Geomatics Sciences, University of Florida, Gainesville, Florida, USA

[3]Spanish Royal Academy of Sciences, Madrid, Spain

[4]USDA Forest Service, Rocky Mountain Research Station, Moscow, Idaho, USA

Correspondence
O. Viedma
Email: olga.viedma@uclm.es

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Abstract

1. Widespread fuel accumulation in various strata is increasing the risk of high-severity, crown-fires. Knowing the vertical forest structure is a crucial factor for fire management planning.
2. Light detection and ranging (LiDAR) sensors have successfully retrieved the main characteristics of the vertical structure of forests. However, detecting and vertically mapping the various fuel strata that can act as ladder fuels (i.e. fuel arrangements that will bring the fire from the surface to the canopy) is challenging and limits our ability to manage the most hazardous forests.
3. Here we show how using LiDAR data and the LadderFuelsR package, developed in the R platform, can provide an automated tool for analysing the vertical fuel structure of a forest and to calculate crown base height (CBH) at tree-level, among other parameters. We include a suite of tools integrated into a sequential workflow for: (1) calculating the leaf area density (LAD) profiles of each segmented tree; (2) identifying gaps and the non-continuous fuel layers present; (3) estimating the vertical distance between fuel layers; and (4) retrieving their base height and depth. Additionally, other functions recalculate previous metrics after considering vertical distances greater than certain threshold and calculates the LAD percentage comprised in each fuel layer removing fuel layers below a specified value. Moreover, it calculates tree's CBH based on three criteria: maximum LAD, and both the largest and the last vertical distance between fuel layers. Additionally, when the LAD profiles showed only one fuel layer with CBH at the minimum base height, it identifies the tree's CBH by performing a segmented linear regression. Finally, a collection of plotting functions is developed to represent all previous metrics.
4. This tool has been tested with different LiDAR sensors and thousands of trees in several *Pinus pinaster* forest areas in Central Spain, and its accuracy has been evaluated using field-based tree CBH in *Pinus palustris* Mills dominated forests in Florida (USA). This tool provides accurate information about the vertical structure

of a forest, which can be used for prioritizing treatment areas to reduce fire hazard or identify high crown-fire risk areas.

KEYWORDS
crown base height, crown fire, fuel gaps, ladder fuels, LIDAR

1 | INTRODUCTION

Fire severity is increasing in many ecosystems across the world (Cunningham et al., 2024) driven by severe weather caused by ongoing climate change (Abatzoglou et al., 2019) and changes in fuel composition and structure that drove fuel accumulation underneath the canopies (Sturtevant & Fortin, 2021). Fuels that connect the ground surface with the canopy are referred to as ladder fuels (Menning & Stephens, 2007) and can significantly influence the occurrence of crown-fires and fire impacts (Forbes et al., 2022). Thus, accurate, spatially explicit information on the characteristics of the fuel layers underneath the tree canopy (depth, biomass and distance to the crown base height [CBH]) are crucial for assessing the likelihood of crown fires and for effective wildfire risk prevention (Agee & Skinner, 2005).

However, challenges persist for accurately determining CBH and the various fuel layers either by using traditional field-based methods, due to the absence of a standardized method (González-Ferreiro et al., 2017), or light detection and ranging (LiDAR) technology due to the presence of multiple fuel layers (Luo et al., 2018). At the individual tree or stand level, LiDAR frequency-based metrics of height (i.e. percentiles) and density metrics have been utilized for estimating field-based CBH (Olszewski & Bailey, 2022), as well as the presence of ladder fuels (Forbes et al., 2022) using regression-based methods. However, their accuracy depends on the precision of the field-based data. Additionally, density metrics for estimating ladder fuels neither permit quantifying the number of fuel layers, nor characterizing their spatial location, length or relationships between them. On the other hand, the analysis of the vertical height profile (VHP), also known as pseudo-wave approach, has been applied for estimating CBH without relying on field measurements and has allowed explicitly capturing the vertical structure of the vegetation (Maguya et al., 2015). However, this approach has shown important limitations in the case of noisy tree vertical profiles, owing to the need of very complex models (Luo et al., 2018; Popescu & Zhao, 2008).

The main objective of this study was to develop a direct, wave-based method to quantitatively characterize fuel layers and gaps beneath trees and to estimate tree CBH using various criteria. The approach is based in using differences in leaf area density (LAD) percentiles between height bins. This package has been tested on different LiDAR sensors across several platforms: (i) Satellite full waveform LiDAR (Global Ecosystem Dynamics Investigation); (ii) airborne discrete return LiDAR with low point density: airborne laser scanner (ALS)-data using the ALS 50-II sensor from the Spanish National Plan of Aerial Orthophotography (PNOA), with an average point density of 0.5 points/m^2 at an altitude of approximately 1000 m (https://pnoa.ign.es/web/portal/pnoa-lidar/especificaciones-tecnicas; accessed on 20 June 2024), and the Leica ALS60 sensor, with an average point density of 6.8 points/m^2 at an altitude of 1200 m (Hudak et al., 2022); and finally, (iii) unoccupied aircraft systems discrete return LiDAR with high point density: LidarPod system using a Velodyne HDL32E sensor with a high point density (>700 points/m^2) at an altitude of 50 m (Viedma, 2022).

2 | PACKAGE DESIGN AND CHARACTERISTICS

LadderFuelsR is an open-source R package for the analysis of the vertical fuel structure of a forest that rests on using LAD profiles from segmented trees (Figure 1). It characterizes the existing fuel layers (base height, depth, LAD percentage and vertical distance between them) and utilizes different methods to identify tree CBH following a sequential workflow (Figure 2).

2.1 | LiDAR data pre-processing

For discrete return LiDAR, after height normalization and crown segmentation, the LiDAR returns were cropped with the crown contours being voxelized to obtain VHPs from which the absolute mean LAD at each height bin was retrieved (de Almeida et al., 2019).

For full Waveform LiDAR, the geolocated return waveforms derived from Level1B product were used (Dubayah et al., 2020). They were filtered by their sensitivity values >0.95 and Quality flag = 1. Moreover, using the relative height percentiles from L2A product, the wave elevation values were converted into vegetation heights. Accordingly, using LadderFuelsR requires the input of a data frame with three columns: an index, the variable to measure (pulse density, pulse amplitude, LAD, intensity, etc.), and the height bins at which these measures are recorded. In this package, LAD percentile thresholds to identify gaps and fuel layer base height are dynamic and customizable using the options '*perc_gap*' and '*perc_base*'. Height bins can vary according to user objectives, set with the '*step*' option (distance between bins, in meters; default 1 m). The minimum height is adjustable via the '*min_height*' option. Additionally, fuel layers separated by specified vertical distances (number of steps to skip) can be reshaped by separating or merging them using the '*number_steps*' option. To determine the presence of a specific fuel layer, this must add more than 10% of the total LAD in the profile (option '*threshold*').

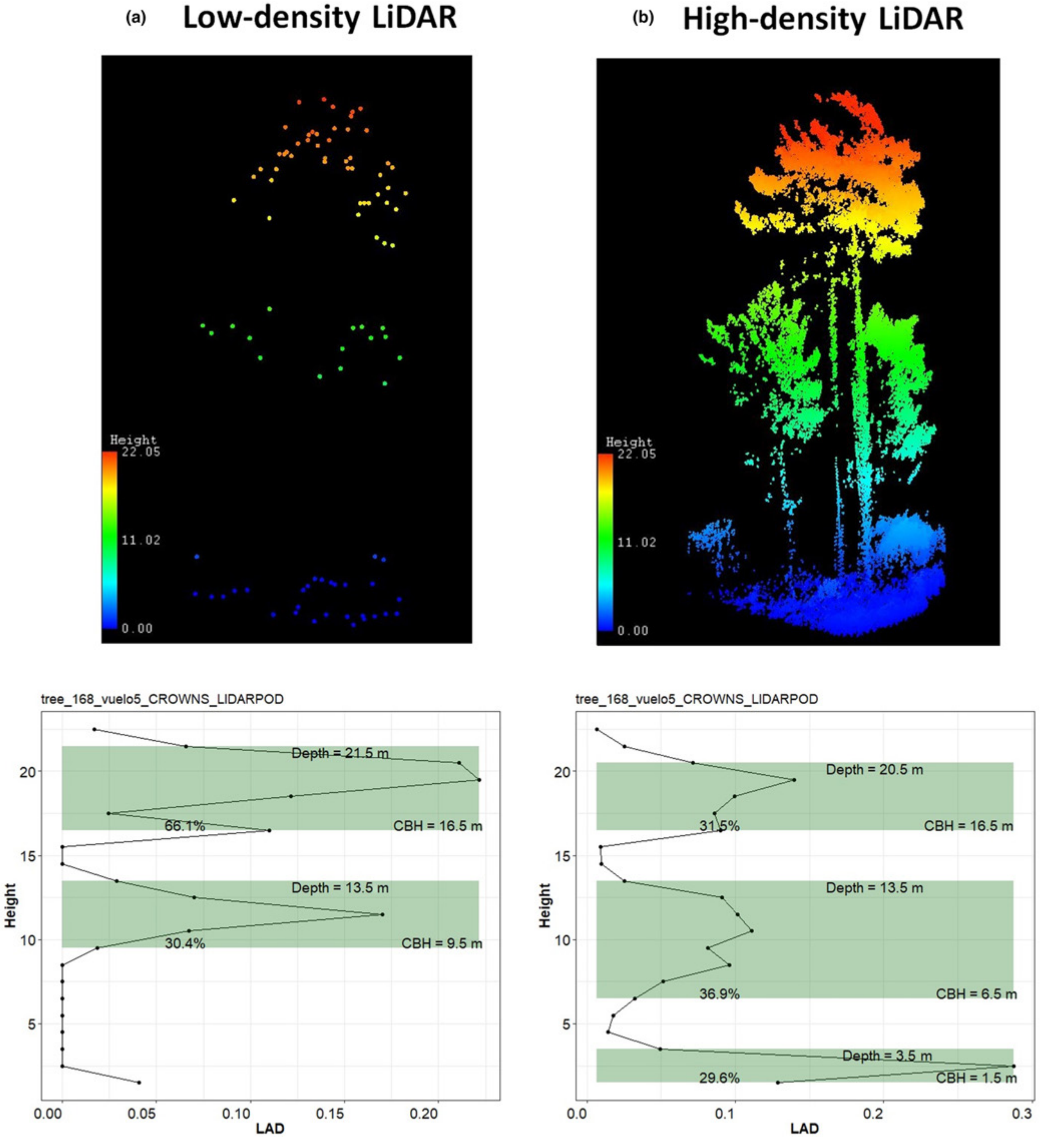

FIGURE 1 Plots of segmented trees and their leaf area density (LAD) profiles with fuel layers in green. For each fuel layer, the crown base height (CBH, m), the depth (m) and the LAD (%) (outputs of LadderFuelsR) are provided. (a) Segmented tree derived from low-density light detection and ranging (LiDAR) and (b) segmented tree derived from high-density LiDAR.

2.2 | Gaps and FBHs for each LAD profile

Function *calculate_gaps_perc()* applies the quantile function to the LAD values at each height bin to calculate percentiles from 5th to 95th, at steps of 5 and percentile 99th, and it classifies the LAD values based on which percentile range they fall into.

Function *get_gaps_fbhs()* identifies height bins with negative differences in LAD percentile for identifying gaps. When among consecutive height bins differences are negative, it selects the height bin with the lowest LAD (≤*perc_gap* [P25th]). Additionally, the function looks for height bins with LAD ≤ P25th, and when they are consecutive, it takes only the first and last values of the set

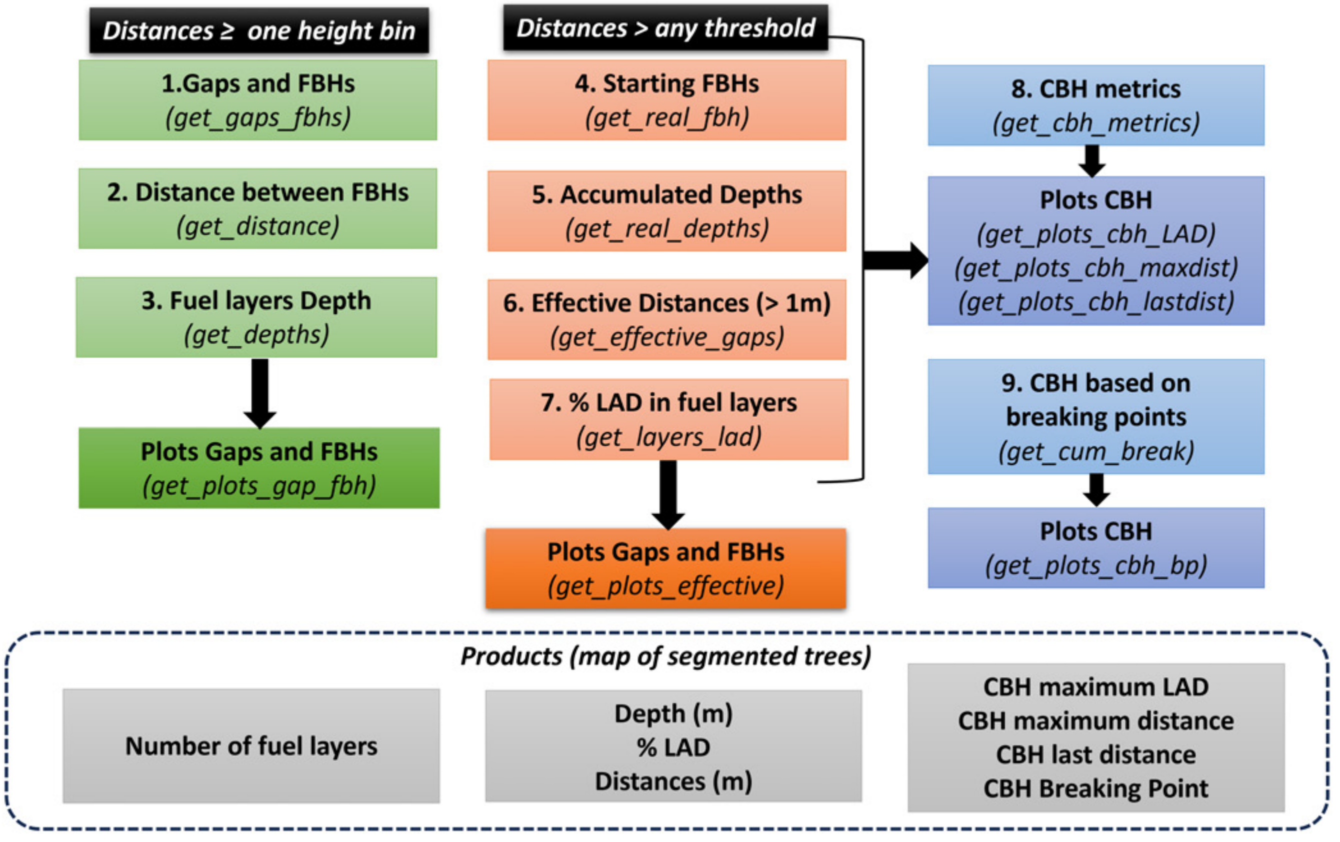

FIGURE 2 Flowchart to yield the products included in the LadderFuelsR package. CBH, crown base height; FBH, fuel base height; LAD, leaf area density.

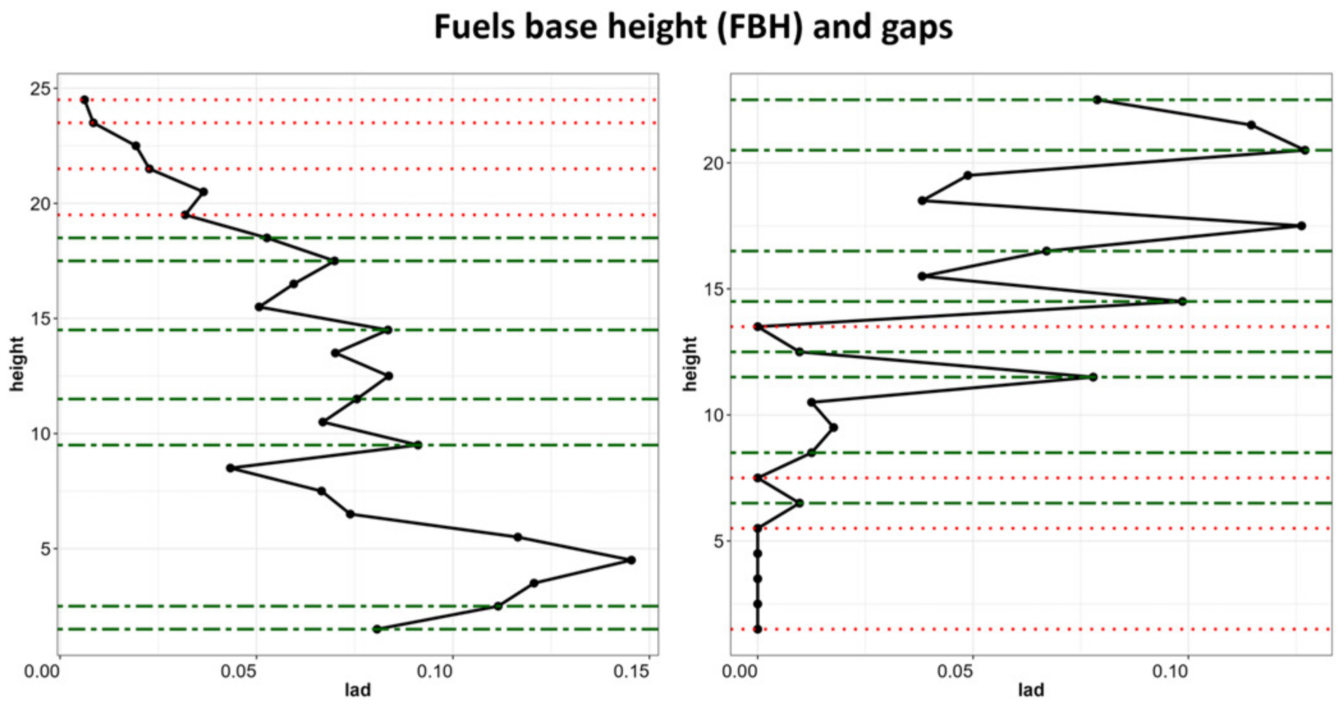

FIGURE 3 Plots of leaf area density profiles with fuel base heights in green and gaps ≥ step: Distance between bins in red.

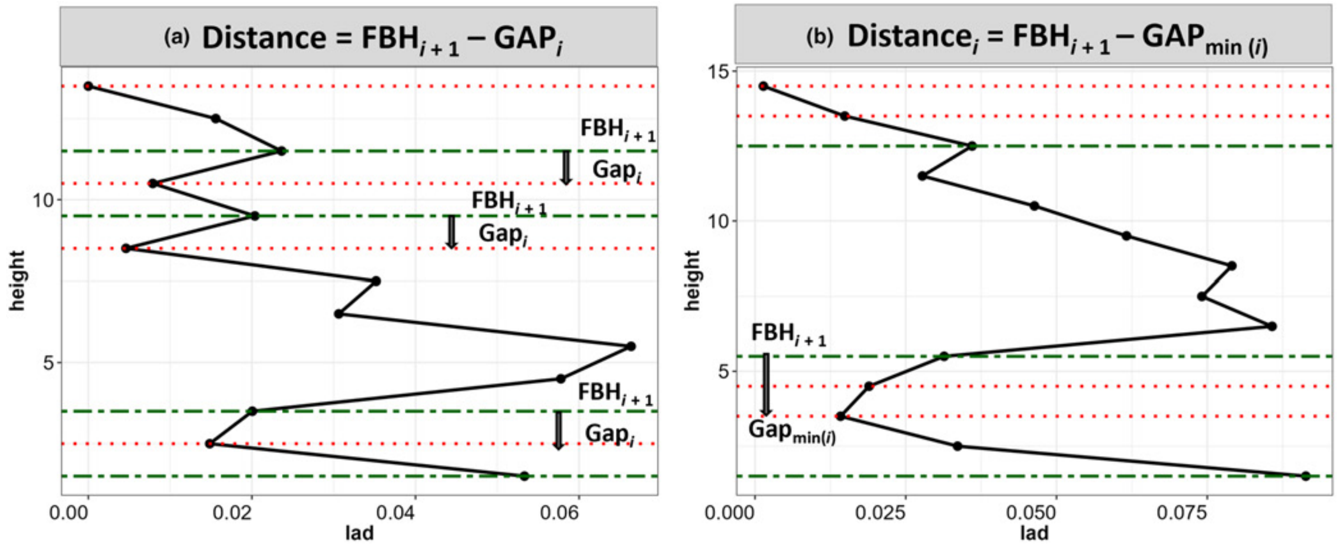

FIGURE 4 Plots of leaf area density profiles for calculating the distance between fuel layers when: (a) there is a single gap; (b) there are consecutive gaps below any fuel base. FBH, fuel base height.

being considered. For obtaining fuel layer base heights (FBHs), it identifies height bins with positive differences in LAD percentile. When such positive differences are consecutive, it selects the height bin with minimum LAD (>*perc_base* [P25th]). Moreover, it filters height bins with LAD > P25th, and when these are consecutive it takes only the first and last values of each set. Finally, to avoid any duplicated height bins in gaps and FBHs, it selects only the height bins identified as gaps that were not present in the FBH file, giving preference to the FBH height bins (Figure 3).

2.3 | Distance between fuel layers

Function *get_distance()* calculates the distance between fuel layers as the height difference between each pair of consecutive gaps and FBHs (Figure 4a). In addition, when there are consecutive gaps, the distance is calculated as the difference between the minimum gap and the next FBH encountered (Figure 4b). Similarly, when there were consecutive FBHs, the distance was calculated as the difference between the minimum FBH and the previous gap encountered. When there are gaps above the last FBH, these values were removed for further analysis.

2.4 | Fuel layer depth

Function *get_depths()* calculates the depth of each fuel layer as the difference between the gaps comprising the FBHs. Finally, to get the real layer depth, and only when layer depth is greater than the step, it subtracts the step value from the depth (Figure 5).

There are special cases when there are no gaps between FBHs: (i) if the gap height is less than the minimum height of the FBHs, depth

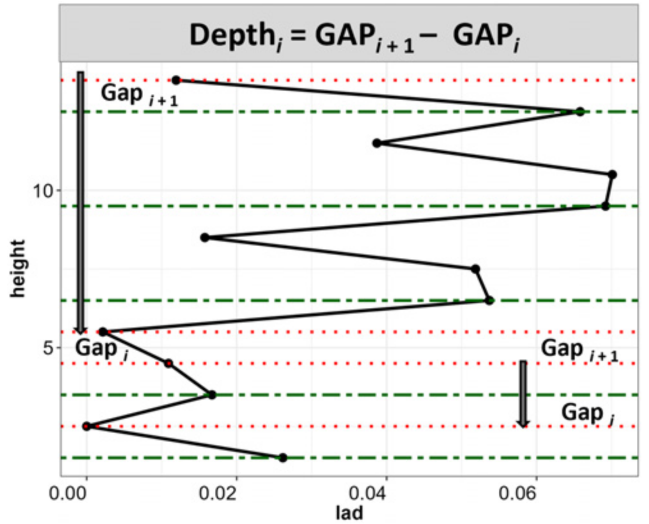

FIGURE 5 Plot of a leaf area density profile for calculating the depth of any fuel layer between gaps.

is calculated as the difference between the maximum height of the FBHs set and the height of that gap minus the step (Figure 6a); (ii) if the gap height is greater than the maximum height of FBHs, depth is the difference between the maximum gap height and the minimum height of the FBHs set minus the step (Figure 6b).

2.5 | FBHs and depth of fuel layers using effective distances

Function *get_real_fbh()* identifies the first FBH from consecutive FBHs or the first FBH from those separated by a distance equal to number of steps that can be skipped to reshape the fuel layers. For each

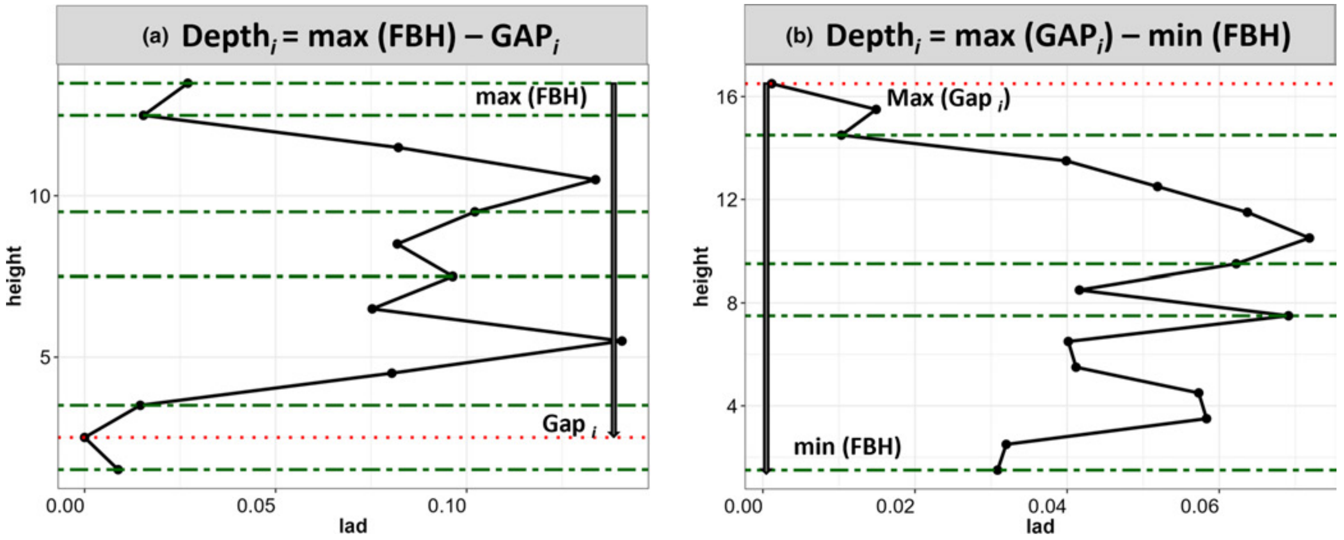

FIGURE 6 Plots of leaf area density profiles for calculating the depth of fuel layers not comprised by gaps: (a) a gap whose height < minimum height of the fuel base heights (FBHs); (b) a gap whose height > maximum height of FBHs.

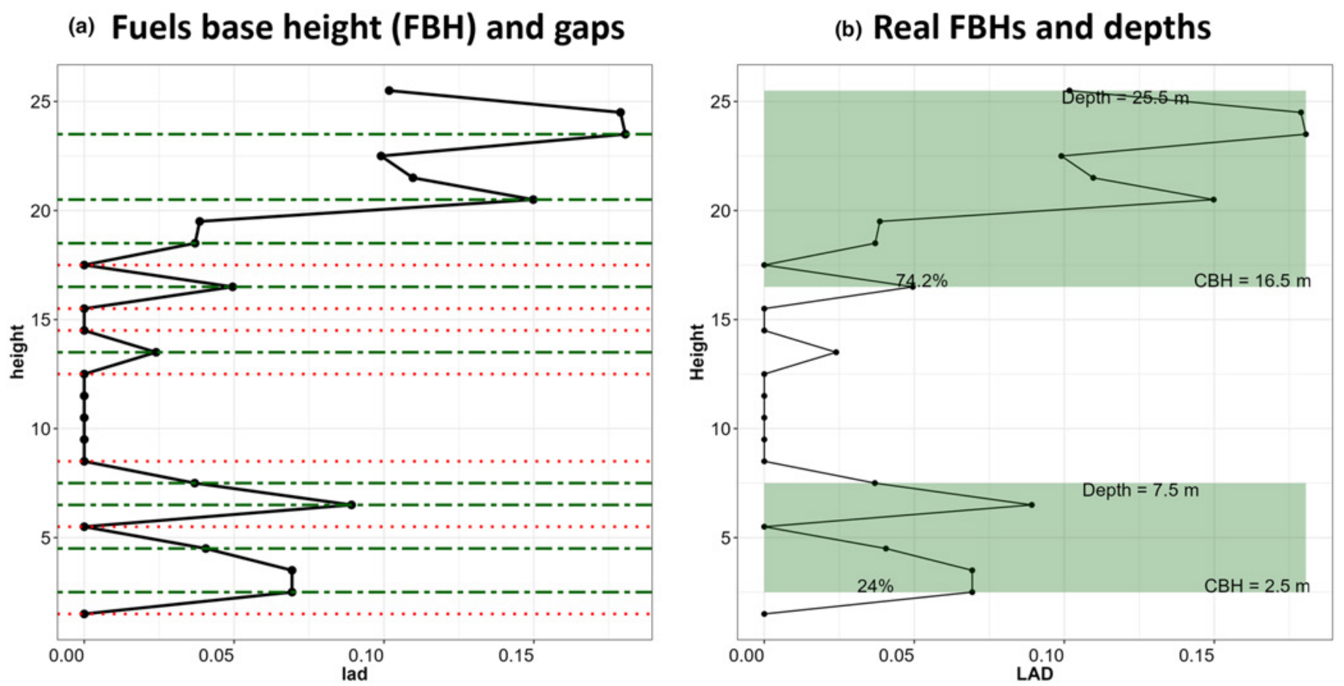

FIGURE 7 Plots of leaf area density (LAD) profiles with (a) fuel base heights (FBHs) in green and gaps in red; (b) real FBHs and depths.

distance value, it locates the next FBH value. If distance = num_step, the height of that FBH is propagated upwards. If distance > num_step, the height of that FBH is kept (Figure 7a,b).

Function *get_real_depths()* calculates the cumulative heights of depth values when distance = num_step. It iterates over each distance value and if $dist_{[i]}$ > num_step, it keeps the corresponding depth value. However, if $dist_{[i]}$ = num_step, it sums all consecutive distances and corresponding depth values (Figure 7a,b).

2.6 | Effective distance between fuel layers

Function *get_effective_gap()* calculates the effective distance between fuel layers based on the previously identified FBHs. It loops over all the FBHs and, at each iteration, it checks if the current value and the next value in FBHs are not equal. If they are not equal, it keeps the corresponding distance value, otherwise it removes it (Figure 8).

2.7 | Effective fuel layers based on the comprised percentage of total LAD

Function *get_layers_lad()* calculates LAD (%) within each fuel layer, which is defined by the height range between the FBH and its depth. First, it calculates the total LAD from the original profile. Next, it retrieves the beginning and end height bin of each fuel layer and calculates the percentage of total LAD that falls within that height range. Later, the fuel layers that had a LAD (%) less than a specified threshold (default 10%) were removed, recalculating the distances (Figure 9).

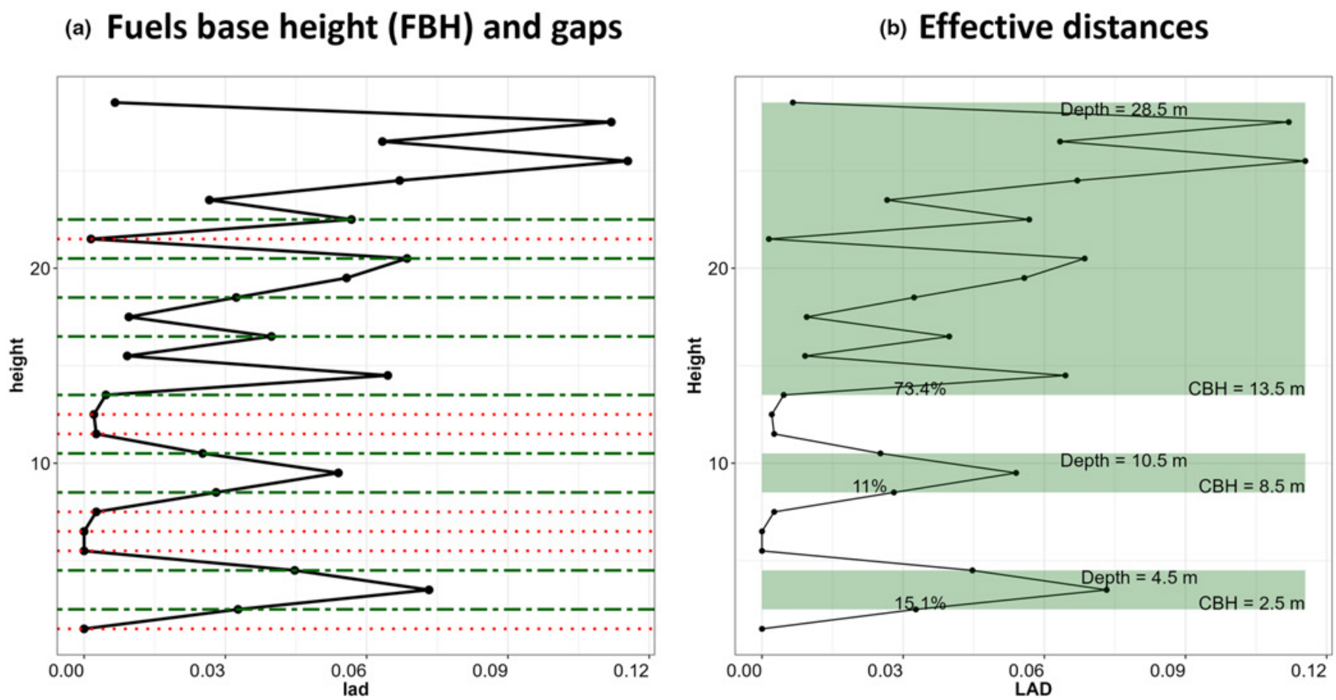

FIGURE 8 Plots of leaf area density (LAD) profiles with (a) fuel base heights in green and gaps in red; (b) effective distances (>number of steps).

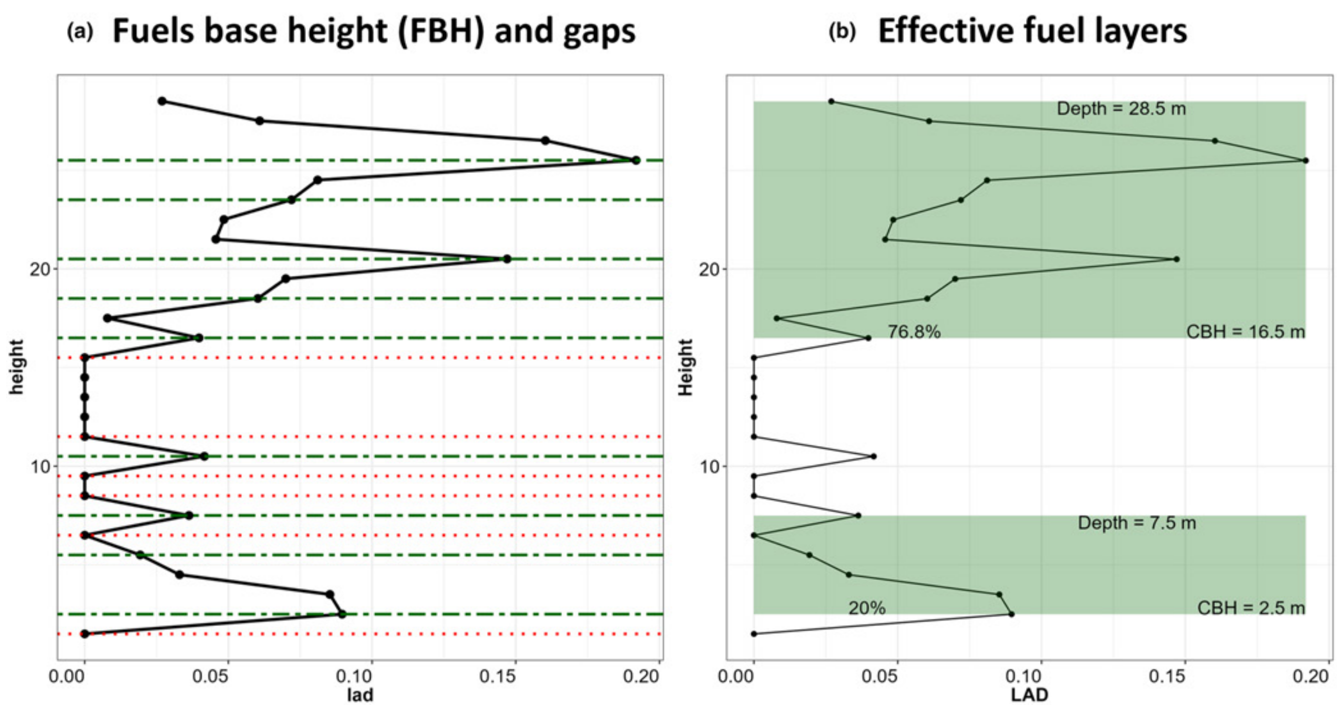

FIGURE 9 Plots of leaf area density (LAD) profiles with (a) fuel base heights in green and gaps in red; (b) effective fuel layers (LAD % >10).

2.8 | Estimation of the CBH based on different criteria

Function *get_cbh_dist()* applies three criteria to define the CBH in a segmented tree: the fuel layer containing the maximum LAD (%) (Figure 10a), the fuel layer located at the highest distance (Figure 10b), and the fuel layer separated by the last effective distance (Figure 10c). In the case of maximum LAD (%), the output also gives the CBH from the second fuel layer when the first one has the maximum LAD (%) but its depth is smaller than the value indicated in the parameter '*hdepth1_height*' (default 2 m). In addition, the function *get_cum_break()* identifies a possible CBH performing a segmented linear regression on the cumulative sum of the LAD values as a function of height. First, the function tries to fit a segmented regression model with an automatic breakpoint (BP) estimation. If the segmented regression model fails, the function resorts to a polynomial regression model. If a valid BP is found, it identifies the height value in the LAD profile closest to this BP as the CBH (Figure 10d) and it calculates the LAD (%) below and above a

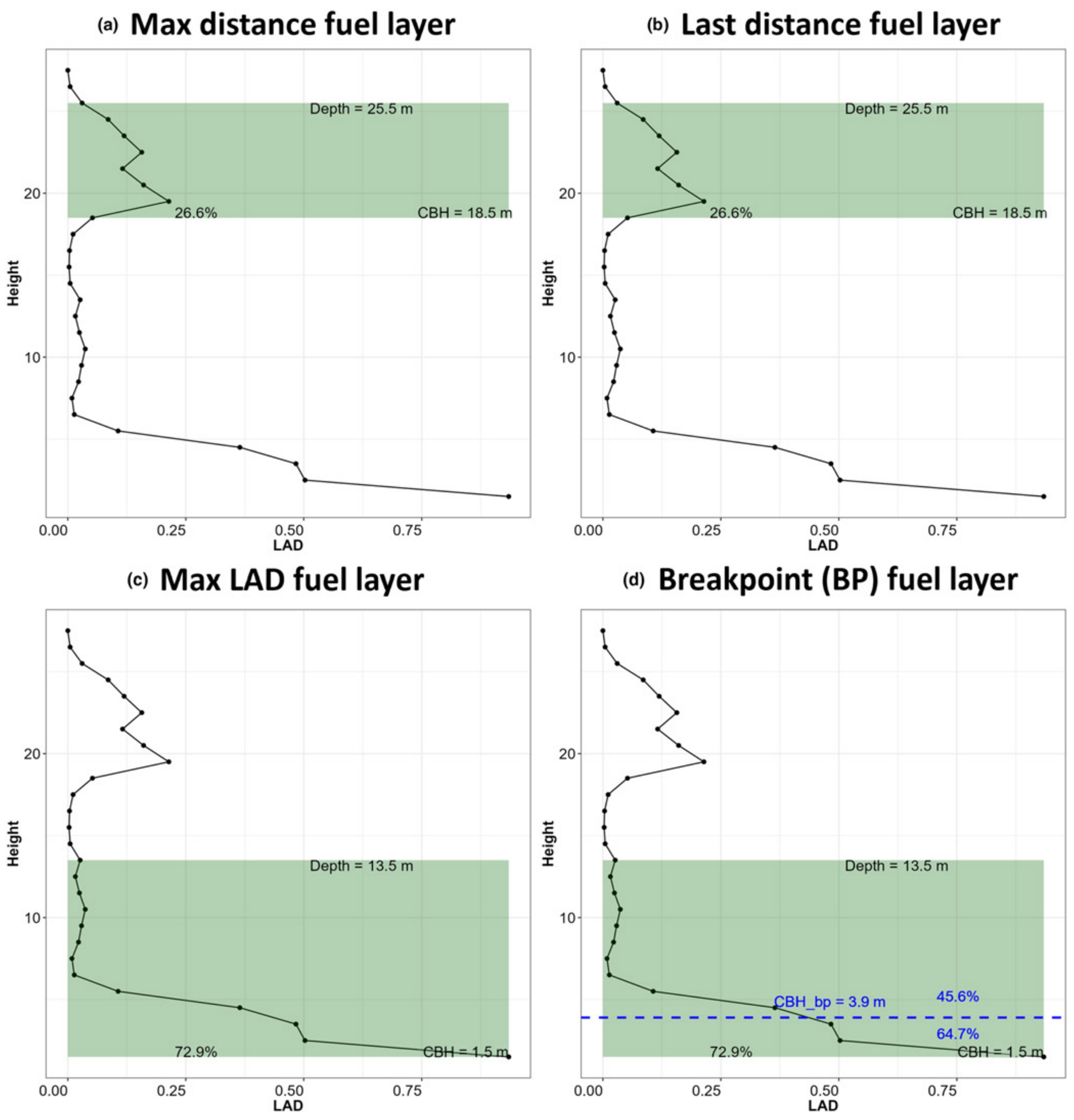

FIGURE 10 Plots of leaf area density (LAD) profiles with the fuel layer identified as the tree crown base height (CBH) following the criteria: (a) maximum LAD, (b) maximum distance, (c) last distance and (d) breakpoint method.

BP. Finally, if the LAD (%) value is above the BP > *threshold* (default 75%), then the CBH value is set to the BP. If LAD (%) is below the BP > *threshold*, the CBH = minimum height; and if the LAD (%) value is <*threshold* in both sides of the BP, then the CBH is assigned from the fuel layer with the maximum LAD (%).

3 | DISCUSSION

Current strategies to manage fires require identifying areas with excessive fuel accumulations. Knowing this is important to prioritize fuel reduction treatments for minimizing high fire-intensity effects and fire-induced tree mortality, hence helping to maintain fire-resilient forests (Regos et al., 2023). How fuels can be arranged vertically to form ladder fuels varies across ecosystems, since various structures can help form the ladders (e.g. unshed dead branches, dead small trees, shrubs, etc.) (Menning & Stephens, 2007). For example, in template pine-dominated forests, like western US coniferous forests, the main ladder fuels are the snags formed by dense understories of suppressed trees (Hessburg et al., 2007). In contrast, in Mediterranean-type forests ladder fuels are mainly drought-tolerant shrubs (Keeley et al., 2011). Moreover, the spatial variability of fuel loads within vegetation types can be as high as that among them, having different effects on fire behaviour (Keane et al., 2012). Accordingly, effective wildfire management involves applying adaptative strategies to the specific fuel characteristics of each forest type.

Here we present an automated and flexible tool for studying of the tree vertical structure of a forest, which can be customized to the needs of the researcher. It is designed for identifying and mapping the various fuel strata that can act as ladder fuels in forests, characterizing the spatial location, length and relationships between them. Comparisons between wave-based and frequency-based models suggest that the wave approach is better for estimating CBH and ladder fuels (Muss et al., 2011). Fitting more complex (multimodal) probability distribution models (Jaskierniak et al., 2011) to the density curve enabled the characterization of highly stratified profiles, although they were computationally intensive. Moreover, different voxelization wave-based methods using terrestrial LiDAR systems have estimated CBH, fuel strata cover (García et al., 2011) and fuel layer volumes (Loudermilk et al., 2009) and can separate crown leaves and wood (Hillman et al., 2021) with high precision due to the high density of points. In addition, the quantitative structural model approach separating fine fuel and coarse fuel (Xi et al., 2023) is promising. Accordingly, all wave-based approaches, independently of the used sensor, are susceptible to be analysed by this package. LadderFuelsR provides some of the parameters needed for fire hazard estimation, such as CBH and fuel vertical continuity. In addition, this application goes beyond fire risk and can be used to study how forest structure can affect biodiversity and wildlife habitat requirements (Goetz et al., 2007).

AUTHOR CONTRIBUTIONS

All the authors have made a substantial contribution towards the successful completion of the package and manuscript. They all have been involved in designing the package, drafting the manuscript and engaging in critical discussion. Olga Viedma coded the package. Carlos A. Silva, Jose Manuel Moreno and Andrew T. Hudak assisted with coding the functions and contributed to the interpretation, quality control and revisions of the package and manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/2041-210X.14427.

DATA AVAILABILITY STATEMENT

The source code of the LadderFuelsR package is accessible via GitHub (https://github.com/olgaviedma/LadderFuelsR). Data are available via https://doi.org/10.5281/zenodo.13523627 (Viedma et al., 2024b). Also, this package can be downloaded from the Comprehensive R Archive Network at https://cran.r-project.org/web/packages/LadderFuelsR/index.html (Viedma et al. 2024a). ALS data and tree data from Eglin forests (Florida, USA) are available at https://www.fs.usda.gov/rds/archive/Catalog/RDS-2015-0010 (Hudak et al., 2022).

ORCID

O. Viedma https://orcid.org/0000-0003-4614-3827
C. A. Silva https://orcid.org/0000-0002-7844-3560
J. M. Moreno https://orcid.org/0000-0002-3729-9523
A. T. Hudak https://orcid.org/0000-0001-7480-1458

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