Prichard *et al. Fire Ecology* (2026) 22:130
https://doi.org/10.1186/s42408-026-00507-2

Fire Ecology

Association for Fire Ecology

BRIEF REPORT

Open Access

Hierarchically scaled remote sensing and field datasets for three-dimensional wildland fuel characterization

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Abstract

Background Next-generation models of fire behavior and smoke production rely on gridded, 3D inputs of wildland fuel complexes. We used a hierarchically scaled sampling design to characterize canopy and surface fuels that are common to prescribed burning programs in the southeastern and western US. Sampling included airborne laser scanning, terrestrial laser scanning, close-range photogrammetry, and destructive field sampling. The objective of this study was to use a combination of airborne laser scanning (ALS), terrestrial laser scanning (TLS), structure-from-motion photogrammetry (SfM), and field observations to create co-located 3D datasets of live and dead understory fuels for use in wildland fuel mapping and prescribed burn decision support.

Results Using our integrated, co-located methods, we detail methods used to produce hierarchically scaled datasets of the structure and composition of canopy and surface fuels across 9 southeastern pine sites, 5 western pine sites, and 4 western grassland sites. These are now publicly available within the Wildland Fire Science Initiative data repository (https://doi.org/10.60594/W4859C).

Conclusions The study demonstrates that 3D fuel characterizations can provide consistently scaled and labeled datasets for model training and evaluation. More specifically, machine learning models can be used to parse 3D point clouds collected from ALS, TLS, and SfM photogrammetry into fuel objects and metrics. Calibration with field plots will allow our hierarchically scaled datasets to be used as the foundation for synthetic fuelbed mapping, starting with fine-scale objects such as individual shrubs or downed wood and scaling to vegetation patches and operational burn units.

Keywords Wildland fuels, Computational fluid dynamics modeling, Longleaf pine, Loblolly pine, Ponderosa pine, TLS, ALS, Structure-from-motion photogrammetry

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Resumen

Antecedentes Los nuevos modelos de comportamiento del fuego y producción de humos se basan en insumos de grillas en 3D derivados de complejos de combustibles vegetales. Usamos un diseño de muestreo jerárquico escalado para caracterizar combustibles superficiales y del dosel superior que son comunes en programas de quemas prescriptas en el sudeste y oeste de los EEUU. El muestreo incluyó escaneo laser aéreo, escaneo laser terrestre, fotogrametría proximal y muestreos destructivos a campo. El objetivo de este estudio fue usar una combinación del escaneo laser aéreo, (ALS), escaneo laser terrestre (TLS), fotogrametría basada en imágenes móviles (SfM) y observaciones a campo, para crear un conjunto de datos localizados en 3 D de combustibles vivos y muertos del sotobosque (superficiales) para ser usados en el mapeo de combustibles y como soporte en la toma de decisiones en quemas prescriptas.

Resultados Usando nuestros métodos integrados y co-ubicados en el terreno, detallamos los métodos usados para producir conjuntos de datos jerárquicamente escalados sobre la estructura y composición de doseles y combustibles superficiales a lo largo de 9 sitios con pinos en el sudeste, 5 en sitios del pinos en el oeste, y en 4 sitios de pastizales en el oeste, todos en los EEUU. Estos datos están hoy públicamente disponibles en el repositorio de datos dentro de la Iniciativa sobre la ciencia de fuegos de vegetación (*Wildland Fire Science Initiative)* (https://doi.org/10.60594/W4859C).

Conclusiones Este estudio demostró que las caracterizaciones de combustibles en 3D pueden proveer de datos consistentemente escalados y etiquetados para demostración como modelos de entrenamiento y evaluación. Más específicamente, los modelos de aprendizaje automático pueden ser usados para analizar y usar nubes de puntos en 3 D coleccionadas de ALS, TLS y fotogrametría móvil, para transformarlos en objetos y métricas de combustibles. La calibración con parcelas a campo permitirá que nuestros datos, jerárquicamente escalados, puedan ser usados como fundamentos para la construcción de mapas de camas de combustibles sintéticas, comenzando con objetos a escala fina como arbustos individuales o vegetación leñosa muerta en superficie y ser escalado a parches de vegetación o unidades operacionales para quemas prescriptas.

Background

Wildland fuel characterization is foundational to understanding and predicting fire behavior, consumption, and smoke with cascading influences on post-fire vegetation dynamics, carbon, and air quality (Keane 2015; Prichard et al. 2022). While all fire behavior and effects models require inputs on wildland fuels, the detail and resolution at which fuels are represented have been typically generalized and represented at coarse spatial scales (e.g., 30-m pixels) and with two-dimensional metrics (e.g., coverage, height and mass per unit area). Wildland fuels are notoriously challenging to quantify because a range of sampling methods are required to measure complex vegetation characteristics along with diverse downed wood, litter and ground fuels. Consequently, field-based estimates often have high levels of uncertainty and variability over space and time (Brown and Bevins 1986; Falk et al. 2007; Keane 2015).

With advances in fire modeling, gridded three-dimensional (3D) characterization of wildland fuels is now possible with important implications for improved wildland fire modeling (Hiers et al. 2009; Loudermilk et al. 2009, 2014). For prescribed fire decision support, the quantification of realistic fuels as continuous variables and their accurate spatial distribution are important to accurately simulate fire behavior, emissions, and smoke impacts (Parsons et al. 2011; Yedinak et al. 2018; Hudak et al. 2020; Loudermilk et al. 2022). Prescribed burns are generally conducted under conservative weather and fuel moisture windows. Due to low flame lengths and fire line intensities under most prescription windows, the amount, type and 3D structure of surface fuels can strongly influence patterns of fire spread and post-fire effects (Hiers et al. 2020).

Models of wildland fire behavior and effects are widely used to inform wildland fire management strategies for prescribed burning and wildland fire operations (Furman 2018; Hiers et al. 2020). Operational fire behavior models in use today such as BehavePlus or the landscape model FARSITE rely on two-dimensional (2D) stylized assignments of canopy and surface fuels (e.g., categorical LANDFIRE fire behavior fuel model layers) that enable rapid landscape assessments. However, they do so at the expense of fine-scale spatial detail and quantified sources of uncertainty (Dickman et al. 2023). Computational fluid dynamics (CFD) models such as FIRETEC (Linn et al. 2002, 2005) and the Fire Dynamics Simulator (FDS, Mell et al. 2007) simulate wildland fire behavior and fire-atmosphere interactions using gridded, 3D meshes of wildland fuel inputs including bulk density, heat content, fuel moisture, and other fuel properties. The QUIC-fire model was developed to more efficiently solve for turbulence and fire behavior than a full physics-based model, using a cellular automaton approach for fire behavior calculations that relies on gridded, 3D fuel inputs (Furman 2018; Linn et al. 2020). Inputs to QUIC-Fire and CFD models are being developed and evaluated within the FASTFUELS platform, which provides onramps for canopy and surface fuels datasets (Marcozzi et al. 2025).

The "3D Fuels Project" was designed to provide foundational wildland fuels data for physics-based fire behavior models that can better inform prescribed fire decision support. The study was conducted in close collaboration with FASTFUELS (Marcozzi et al. 2025) to develop methods for characterizing fuels in 3D and provide inputs to physics-based models of fire behavior and effects. Our objective was to use a combination of airborne laser scanning (ALS), terrestrial laser scanning (TLS), structure-from-motion photogrammetry (SfM), and field observations to create hierarchically scaled, 3D point cloud datasets of live and dead understory fuels to inform the scaled mapping of 3D fuels across the open forest types in which most prescribed burns are conducted. To inform models that parse these 3D point cloud datasets into segmented objects and metrics (e.g., height, cover, bulk density), we co-located intensively sampled 3D calibration plots with ALS, TLS, and SfM scans across 18 sites in the southeastern and western US (Table 1).

Methods

Sampling design

We employed a hierarchical sampling design for mapping 3D surface and canopy fuels that relied on a combination of airborne and high-resolution terrestrial laser scanning (ALS and TLS), structure-from-motion photogrammetry (SfM), and ground-based measures of physical fuel

Table 1 3D Fuels study site locations, descriptions, and sampling dates. *TSF* time since fire

Site	Location	TSF/biomass	Vegetation type	Sampling date
Southeastern flatwood forests				
Aucilla	Suwannee River Water Management District, FL	> 5 years	Longleaf pine—high load saw palmetto and gallberry	April 2021
Blackwater	Blackwater State Forest, FL	2 years	Open longleaf pine forest—wiregrass understory	August 2019
Ft Stewart	Fort Stewart, GA	1–2 years	Open longleaf and loblolly pine forest—moderate load saw palmetto and gallberry	January 2022
Osceola	Osceola NF, FL	1–2 years	Open longleaf pine forest—low load palmetto and gallberry	January 2020
Tate's Hell A	Tate's Hell State Forest, FL	1–2 years	Slash pine plantation – low load saw palmetto and gallberry	January 2020
Tate's Hell B	Tate's Hell State Forest, FL	2–3 years	Slash pine plantation – moderate load saw palmetto and gallberry	January 2020
Loblolly-sweetgum forests				
Hannah Hammock	Tall Timbers Research Station, FL	1–2 years	Loblolly pine plantation—sweetgum understory	July 2022
Hitchiti A	Hitchiti Experimental Forest, GA	2–3 years	Loblolly pine plantation—sweetgum understory	February 2022
Hitchiti B	Hitchiti Experimental Forest, GA	1 years	Loblolly pine plantation—sweetgum understory	February 2022
Western ponderosa pine forests				
LANL Forest	Los Alamos National Laboratory, NM	Low	Open pine forest—sparse Gambel oak and timber-litter	June 2021
Lubrecht	Lubrecht Experimental Forest, MT	High	Open pine and mixed conifer forest—timber litter-shrub understory	July 2019
Methow	Methow Wildlife Area, WA	Moderate	Open pine forest—bitterbrush and timber-litter	October 2021
Sycan Forest I	Sycan Marsh Preserve, OR	Low	Open pine forest—bitterbrush and timber-litter	September 2019
Sycan Forest II	Sycan Marsh Preserve, OR	Low	Open pine forest—bitterbrush and timber-litter	October 2021
Western grasslands				
Glacial Heritage	Glacial Heritage Preserve, CNLM, WA	High	High biomass nonnative grassland	July 2020
LANL Grassland	Los Alamos National Laboratory, NM	Low	Sparse, dry grassland	June 2021
Sycan Grassland	Sycan Marsh Preserve, OR	Low	Sparse grassland with grazing	September 2019
Tenalquot	Tenalquot Prairie Preserve, CNLM, WA	Moderate	Native prairie grassland	July 2020

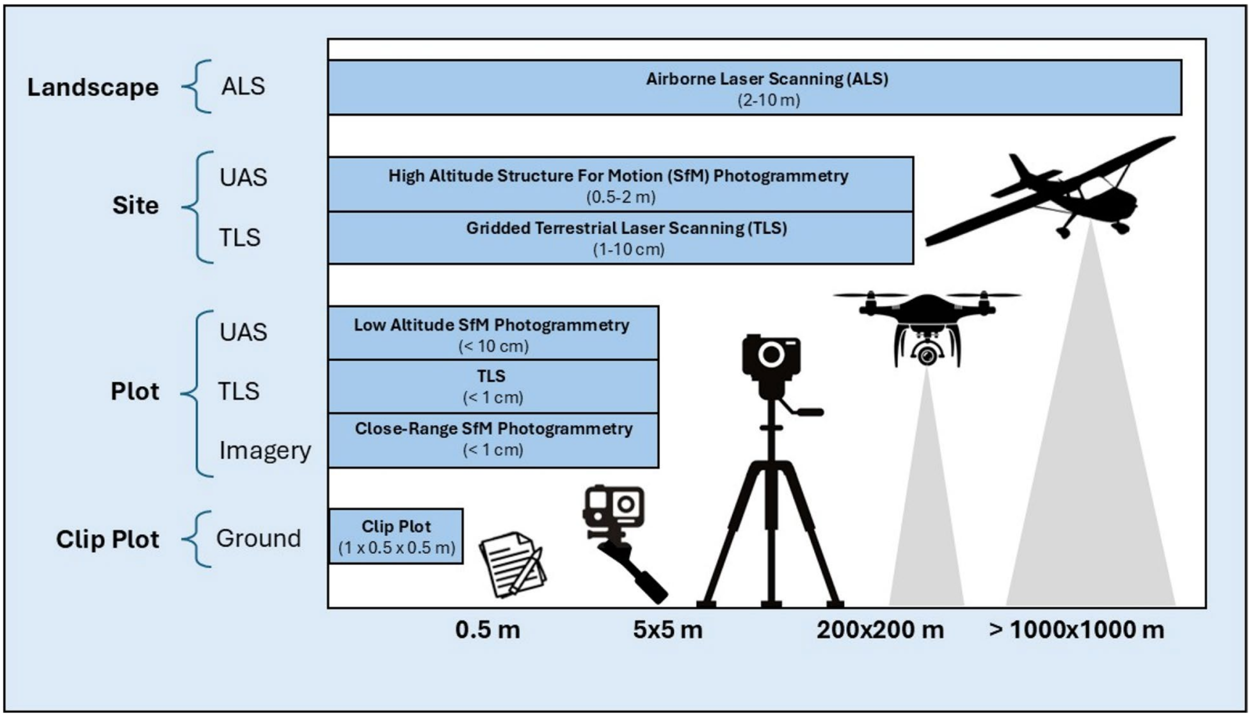

Fig. 1 Hierarchical sampling design of the 3D Fuels study. Study plots were sampled starting from a coarse resolution (ALS at 2–10 m resolution) down to increasingly refined scales (UAS and TLS at sub-meter resolutions), and ultimately to a fine scale (sub cm resolution) at the 0.5 to 0.5 plot level

properties, including destructive sampling within a 3D grid (Fig. 1). The purpose of this design was to facilitate the production of 3D maps of surface and canopy fuels across a range of spatial scales and vegetation types that function as inputs for CFD models and other process-based fire-atmosphere models that rely on gridded fuel inputs. Because airborne lidar datasets are scanned across larger domains, they are capable of mapping vegetation at larger spatial scales than terrestrial laser scanning and close-range photogrammetry. The hierarchical sampling design is thus intended to inform higher-resolution characterization and modeling of forest understories and grasslands. Field-based measurements include estimates of occupied volume and biomass to evaluate relationships between point cloud metrics and measured structure and biomass.

Study areas

This study includes a total of 18 sites, including 9 locations in southeastern mesic flatwood sites ($n=5$) and loblolly pine-gallberry plantations (*Pinus taeda-Ilex glabra*; $n=3$) in the southeastern US and 9 locations in mixed conifer/pine forests ($n=5$) and grasslands ($n=4$) in the western US (Figs. 2 and 3). Forested sites had open pine-dominated canopies with understory fuel complexes ranging from low to relatively higher biomass within each of three major forest types: southeastern pine forests (including loblolly, longleaf (*P. palustris*), and slash pine (*P. elliottii*)) with flatwood understories, southeastern loblolly plantation forests with sweetgum (*Liquidambar styraciflua*) understories, and semi-arid western ponderosa pine (*P. ponderosa*) forests with litter-shrub understories. Although geographically distinct and with markedly different climates and species composition, fire-maintained southeastern and western pine forests share structural similarities (e.g., single-story, open canopied forests with grass, shrub, and litter understories). Our methods to characterize canopy and understory fuels may be broadly applied in mapping and to generate 3D model inputs. Specifically, we anticipate that because these open pine forests have similar structural characteristics, scripting algorithms can be used to reduce point-cloud data into volumetric pixels (termed voxels) for many southeastern and western pine forests.

Southeastern pine sites were selected to represent a range in understory biomass from low biomass (e.g., a 1-year time since fire, TSF) to high biomass (e.g., 4–5 year TSF). Due to less frequent burning, ponderosa pine forest and western grassland sites were selected to represent a range of biomass instead of TSF (Table 1). Selection criteria for all sites included availability of recent

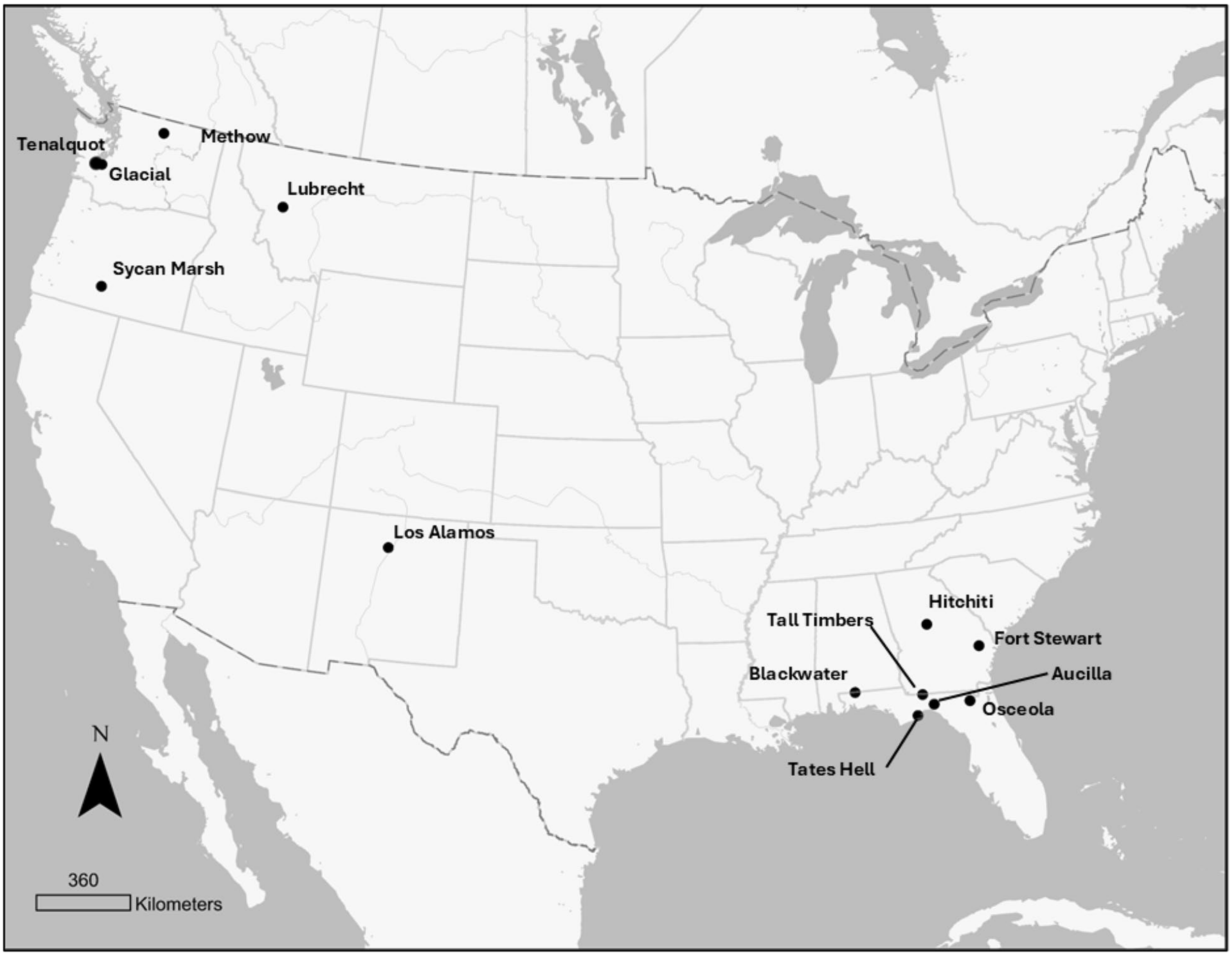

Fig. 2 Site locations for the 18 study sites in the 3D Fuels project.An interactive map is available at https://arcg.is/1jTz9y0

ALS acquisitions and relatively uniform ground surface on gradual slopes (< 30% gradient).

Southeastern flatwoods

The *Fort Stewart* site was a part of a large collaborative experimental burn conducted at Fort Stewart Army Base, Hinesville, GA. The site is a flat, mesic coastal plain forest with an overstory of longleaf pine and slash pine and an understory of low evergreen shrubs and bunchgrass. Prescribed burns are conducted every 2–3 years. The site was burned on March 2, 2022 and resampled immediately post burn. *Tate's Hell A* is located in a mesic slash pine forest that was burned approximately one year prior to sampling with an understory dominated by saw palmetto (*Serenoa repens*) and gallberry. *Tate's Hell B* has similar vegetation with more than two years of growth since fire. *Aucilla* is a mesic flatwood site located in the Middle Aucilla Conservation, FL and has not been burned in more than 5 years. It has an open longleaf pine canopy with an understory of saw palmetto and ferns with deciduous shrubs, oak sprouts, and grasses. *Blackwater* is located within the Blackwater River State Forest, FL and has an overstory dominated by longleaf pine with a wiregrass (*Aristida stricta*) dominated understory with scattered saw palmetto and other native shrubs. *Osceola* was sampled as part of a long-term USFS fire interval study in Osceola National Forest, FL (Ross et al. 2024). The site has a longleaf pine overstory with saw palmetto, gallberry and blueberry (*Vaccinium* spp.), wiregrass, and bunchgrasses in the understory. Our sampling design was modified here to coordinate with a fuel consumption study (Ross et al. 2024).

Southeastern loblolly-sweetgum forests

Hannah Hammock is located at Tall Timbers Research Station, FL and is burned every 2–3 years. The overstory is composed of loblolly and shortleaf pine (*P. echinata*) with a diverse understory of shrubs and herbs.

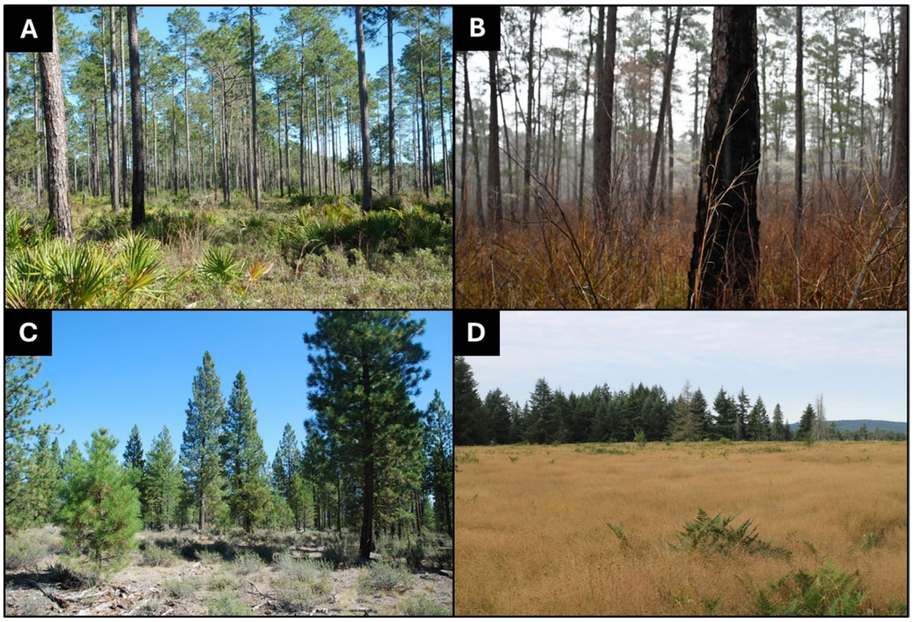

Fig. 3 Representative site photos from each vegetation type surveyed as part of the field campaign of the 3D Fuels project. Photo A: southeastern US pine forest with mesic flatwood understory *(Tates Hell B, FL)*; Photo B: loblolly pine plantation with sweetgum understory *(Hitchiti B, GA)*; Photo C: western ponderosa pine forest *(Sycan Forest, OR)*; Photo D: western grassland *(Tenalquot, WA)*

Hitchiti A and B are located within upland sites in the Hitchiti Experimental Forest in Oconee National Forest, GA. Overstories are dominated by loblolly pine with an understory of mixed grasses and forbs and sprouting hardwoods. *Hitchiti A* represents 2–3 year TSF with moderate sweetgum cover in the understory, and *Hitchiti B* represents 1 year TSF with a dense sweetgum understory.

Western pine and mixed conifer forests

The *LANL forest* site, located at Los Alamos National Laboratory (LANL), NM, is a dry ponderosa pine site intermixed with Gambel oak (*Q. gambellii*) and occasional southwestern white pine (*P. strobiformis*) with a sparse understory of scattered oak sprouts and grasses and occasional deciduous shrubs. *Sycan Forest I* and *II* sites were sampled in coordination with prescribed burning campaigns in the fall of 2019 (*Sycan Forest I*) and 2020 (*Sycan Forest II*) at The Nature Conservancy's Sycan Marsh Preserve, OR. The site has an open canopy and uneven-aged ponderosa pine forest, with evidence of past logging and thinning with an understory dominated by scattered bitterbrush (*Purshia tridentata*) and grasses. It was burned shortly after our pre-fire sampling campaign, with immediate post-burn sampling. The *Methow* site is a young (< 50 year) ponderosa pine forest within the Methow Wildlife Area, WA (Washington Department of Fish and Wildlife). The unit is in a moderately open ponderosa pine forest with scattered bitterbrush understory, pine needle litter, and downed wood. The *Lubrecht site* is located within University of Montana's Lubrecht Experimental Forest in western Montana. The overstory consists of ponderosa pine and Douglas-fir (*Pseudotsuga menziesii*) with sparse understory vegetation dominated by scattered low shrubs including huckleberry (*Vaccinium* spp.) and kinnikinnick (*Arctostaphylos uva-ursi*). The site was mechanically thinned during the winter of 2001 as part of the Fire and Fire Surrogates Project (Hood et al. 2024) and last burned in 2002.

Western grasslands

The *LANL grassland* site is located just outside of the northern boundary of LANL, NM and consists of invasive, low productivity grasses and forbs. Scattered juniper (*Juniperus monosperma*) and Gambel oak occur, with ponderosa pine on the perimeter. The *Sycan grassland* site is located in a dry, heavily grazed meadow with sparse bunchgrasses, forbs and other graminoids within Sycan Marsh Preserve. As with the Sycan Forest site, sampling included pre- and post-burn measurements. The *Tenalquot* and *Glacial Heritage* sites are managed by the Center for Natural Lands Management (CNLM) and located in southwestern Washington state. *Tenalquot* is a moderately invaded native bunchgrass prairie. *Glacial Heritage* is dominated by invasive grasses and herbs.

Field methods

Plots were installed along a grid with 50-m spacing between grid points (Fig. 4). The most common unit layout included points that were set on a 200×200-m grid, but grid shapes were adjusted to accommodate unit dimensions and to avoid wetlands, streams, roads, other developed features, and steep slopes. Within each site, a minimum of thirteen of the grid points were randomly selected for higher-resolution scanning; 9 of these were selected for TLS and close-range photogrammetry scanning coupled with destructive biomass sampling, while a minimum of 4 points were selected for scanning alone. Plots were monumented using four 2-m long metal conduit poles topped with a band of reflective tape, one in each corner of a 5×5-m plot. For destructive sampling plots, an additional 5 poles were used to mark interior points which served as the northwestern corners of 0.5×0.5-m destructive sampling plots, referred to as "clip plots." Five clip plots were distributed in a grid formation within the larger plot, and labeled NW, NE, CTR, SW and SE for the cardinal pattern in which they were distributed (Fig. 4 inset). PVC squares measuring 0.5 m on each side were wrapped in reflective tape and used to mark boundaries of each clip plot on the ground. Reflective tape on poles and PVC squares facilitated identifying the location of clip plots in lidar and SfM imagery. Photos were taken of each clip plot prior to destructive sampling.

Terrestrial laser scanning and structure-from-motion photogrammetry

Terrestrial laser scanning (TLS) was conducted using a RIEGL-VZ2000 TLS at most sites; a RIEGL-VZ400i was used when the VZ2000 unit was unavailable to scan the Fort Stewart and Hitchiti A and B units. Both scanners had a sampling rate of 750 kHz with a scan line density of 0.21 degrees. Scanners were mounted on a tripod at a minimum height of 1.5 m. Location, bearing, and tilt of scanner were recorded using an integrated L1 GPS receiver, compass, and inclination sensors. Scans were completed at each of the 25 gridded points within each site for creation of a site-level synoptic point cloud. At the 13 randomly selected grid points where 5×5-m plots were established, TLS scan was captured on each of the 4 sides of every 5×5-m plot, from a position located at the center point of each side and approximately 1.5 m from plot edge (Fig. 4).

Where permitted, unoccupied aerial systems (UAS) were used to collect imagery at both low (plot-level capture) and high altitudes (synoptic site-level capture) to be used in SfM modeling (Table S1). UAS-based imagery was the only dataset not collected on all sites and without standardization of methods. Dense vegetation in some forested sites (Aucilla, Hannah Hammock, LANL Forest and Methow) prevented the collection of low-altitude imagery. Several different UAS were used, including a DJI Matrice 100 and DJI Mavic Pro. Synoptic flights were flown using fully automated flight planning software at 100-m above ground level in a gridded pattern, with a

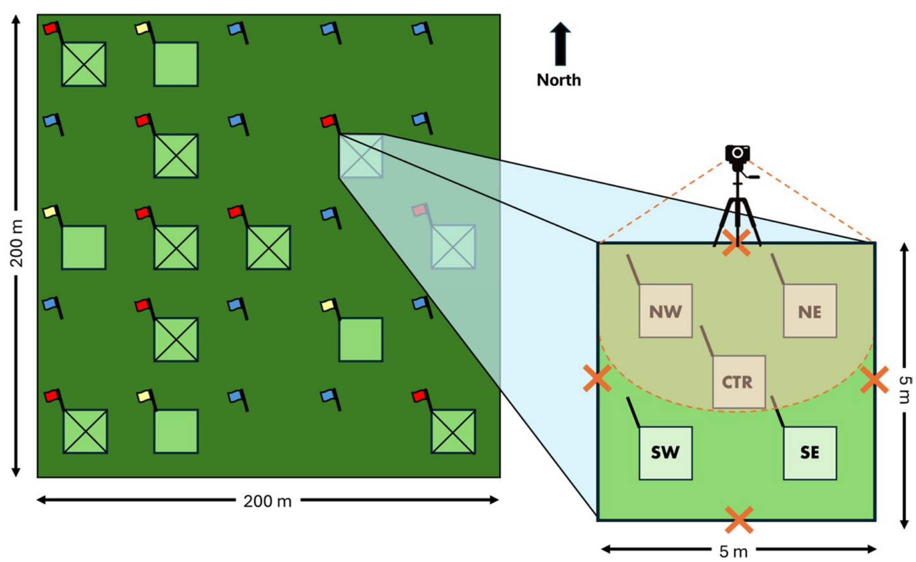

Fig. 4 Schematic image of the standard plot layout used in the 3D Fuels study: 200×200-m grid with nine 5×5-m plots selected for intensive scanning coupled with destructive sampling (red flags and black "X"s) and four selected for intensive scanning without destructive sampling (yellow flags). Blue flags represent remaining grid points used for synoptic (single point) scans. Inset details the ordinal layout of the 5 clip plots. Four TLS scans were taken at each 5 x 5-m plot, which are marked by red and yellow flags. Intensive TLS scanning locations are marked with orange "X"s in the clip plot inset

targeted overlap of 80%. Flight line directions and total number of images were dependent on site logistics. Plot-level flights were flown manually at approximately 3-m height in a spiral pattern with additional external oblique images taken facing toward the plot center. Ground control points were marked with coded black and white targets. Coordinates of these were recorded using an RTK/Differential GNSS receiver/base combination. Ground control points were put precisely at the NW corners of plots in order to tie the high-altitude drone acquisitions to the low-altitude acquisition.

Close-range photogrammetry was collected using a GoPro Hero7 camera mounted on a Feiyu G6 Gimbal, which was then threaded onto a 36-inch pole. A 1–2 min video was filmed from a constant 1-m elevation maintaining a consistent snaking pattern above each clip plot. Camera pixel resolution was set at 2700 K, with a frame rate of 60 frames per second. A second snaking pattern was repeated at a 90° angle to the first, and finally the entire plot was circled with the camera at an oblique angle pointed inward to the plot. Printed targets and foam tubes were placed around each plot for use as alignment markers in the imagery.

Clip plot sampling

A 3D PVC frame was used to sample the occupied volume of fuels by major fuel type and for destructive sampling (Fig. 5) (Hawley et al. 2018). The PVC frames measured 0.5 m on each side and 1 m in height and were divided into 250 voxels, with a sliding square that was used to delineate a single stratum gridded with wire: each 10-cm of height was considered a stratum (e.g., 0–10 cm, 10–20 cm, 20–30 cm). As the sliding square was placed at the level of a stratum, it was divided into 25 voxels using 0.5 m long rigid wires; voxels are numbered 1–25 on the lowest stratum and increase with each higher stratum, reaching 250 on the 90–100 cm stratum. Major fuel types were identified and marked as present or absent for each voxel (Fig. S1). If a trace amount of voxel space was occupied, presence in that voxel was not recorded. Plant material was categorized into one of nineteen groups, termed fuel elements (Table 2). Some elements were further divided into subcategories where fuel properties differ widely within element groups, such as deciduous versus evergreen shrubs.

Biomass sampling generally occurred immediately after scanning and documentation (i.e., photography, TLS, and SfM photogrammetry) were completed. In sites that were part of prescribed burn studies (Sycan Forest, Osceola, and Fort Stewart), presence/absence data were recorded in half of the plots (selected at random) without destructive sampling before burns (designated ‘pre-fire non-destructive plots’). The other half of the plots were destructively sampled before burning (pre-fire destructive plots) and the remainder were clipped after the burns were completed (post-fire destructive plots). For plots where biomass was sampled, vegetation was collected beginning at the highest stratum present and continued until the mineral soil layer was exposed. Within the 0–10 cm stratum, 5 voxels were randomly selected to be sampled individually, and the remainder of the stratum was collected as a unit. Where duff was present, this material

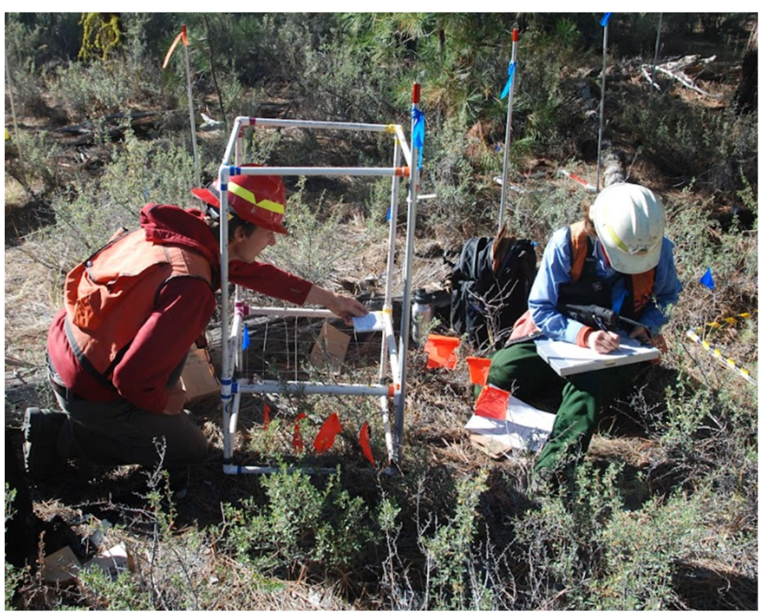

Fig. 5 Example of clip plot methods using a 3D sampling grid at Sycan Marsh Preserve, OR with a sliding frame to allow for volumetric sampling of each vertical 10-cm stratum. Details on this approach are provided in (Hawley et al. 2018). Photo credit: Susan Prichard

Table 2 Fuel elements used to categorize vegetation during field sampling for the 3D Fuels project. Several elements (e.g., woody leaves/litter) have subcategories to allow finer distinctions (e.g., deciduous vs. evergreen leaves). Fuel elements were grouped into broader fuel types for analysis of plot metrics based on dominant fuels, such as fine and coarse woody debris (FWD and CWD, respectively). *NA* not applicable

Fuel element	Subcategories	Fuel type
Woody live shrubs/trees	Deciduous, evergreen, deciduous oak, evergreen oak, mixed oak, mixed evergreen, mixed deciduous, mixed	Shrub and small tree
Woody leaves/litter	Deciduous, evergreen, deciduous oak, evergreen oak, mixed oak, mixed evergreen, mixed deciduous, mixed	Forest floor
Woody standing dead shrubs/trees including conifers	NA	Shrub and small tree
Conifer live seedling/saplings	NA	Shrub and small tree
Vines (and vine litter)	NA	Shrub and small tree
Wiregrass/bunchgrass	Wiregrass, bunchgrass, mixed	Herbs
Other graminoids	NA	Herbs
Forbs (and forb litter)	NA	Herbs
1-h fuel	NA	FWD
10-h fuel	NA	FWD
100-h fuel	NA	FWD
1000-h + fuel	NA	CWD
Pine cone	NA	Forest floor
Conifer litter (bark flakes, pollen cones, other needles)	NA	Forest floor
Pine needles	Long, short, mixed	Forest floor
Duff (partially to fully decomposed litter)	NA	Forest floor
Other	Acorns, insect exoskeletons, moss/lichen, mushroom, scat	Forest floor

was separated from litter in the field and collected separately. As a supplement to vegetation data from clip plots, we collected additional forest floor material at each site for use in bulk density measurement and modeling efforts. Plots were arranged around trees adjacent to each of the destructive sampling plots. Detailed methods are available in Prichard et al. (2025).

Image processing

Recent ALS datasets were acquired for each site to provide synoptic measures of vegetation structure (Table S2). When necessary, raw scans in binary LAS format were merged for complete site coverage, and the 200 × 200-m site area (with a 50-m buffer) was clipped to create a smaller single point cloud in compressed LAS (LAZ) format to be used in analyses. Each point within xyz point clouds was classified as ground or non-ground, and non-ground point heights were normalized to heights above ground using the lasground_new function of the LAStools software package (version 230821, https://rapidlasso.de; Gilching, Germany). Noise points were removed using a nearest neighbor filter function (nnFilter function in the TreeLS package in R (R Core Team 2024). A digital terrain model (DTM) was also created for each site by interpolating ground points with the blast2dem function of LAStools.

Synoptic TLS point scans were imported as a single project for each site using RiSCAN PRO (www.riegl.com; Horn, Austria), the proprietary software designed for use with Riegl scanners. All point scans were registered and georeferenced using this software, then exported as individual LAZ files. Grid-point scans were merged into larger blocks, or tiles, which were created to span the entire 200 × 200 m site with a 5-m overlap on each. The 4 scans taken at each 5 × 5-m plot were merged into a single point cloud of the 5 × 5-m area, and clipped to the plot boundaries with a 3-m exterior buffer.

Individual 0.5 × 0.5 × 1-m clip plots were clipped from the larger 5 × 5-m point clouds using a R shiny application (R Core Team 2024). This semi-automated process uses the high reflectivity of the conduit poles and taped PVC frames in the point clouds to identify the clip plot boundaries and segment those points out of the larger point clouds (Fig. S2).

We used a combination of python scripting and Agisoft Metashape Pro version 1.7.2 (www.agisoft.com) to create accurate 3D point clouds from handheld videos. Because synoptic UAS photogrammetry was not sampled across all sites, only raw imagery is supported within the WFSI repository. Python scripting was used to transform field-recorded videos into a series of still images while filtering out low-quality or irrelevant images. Once this step was completed, a technician reviewed the still images to

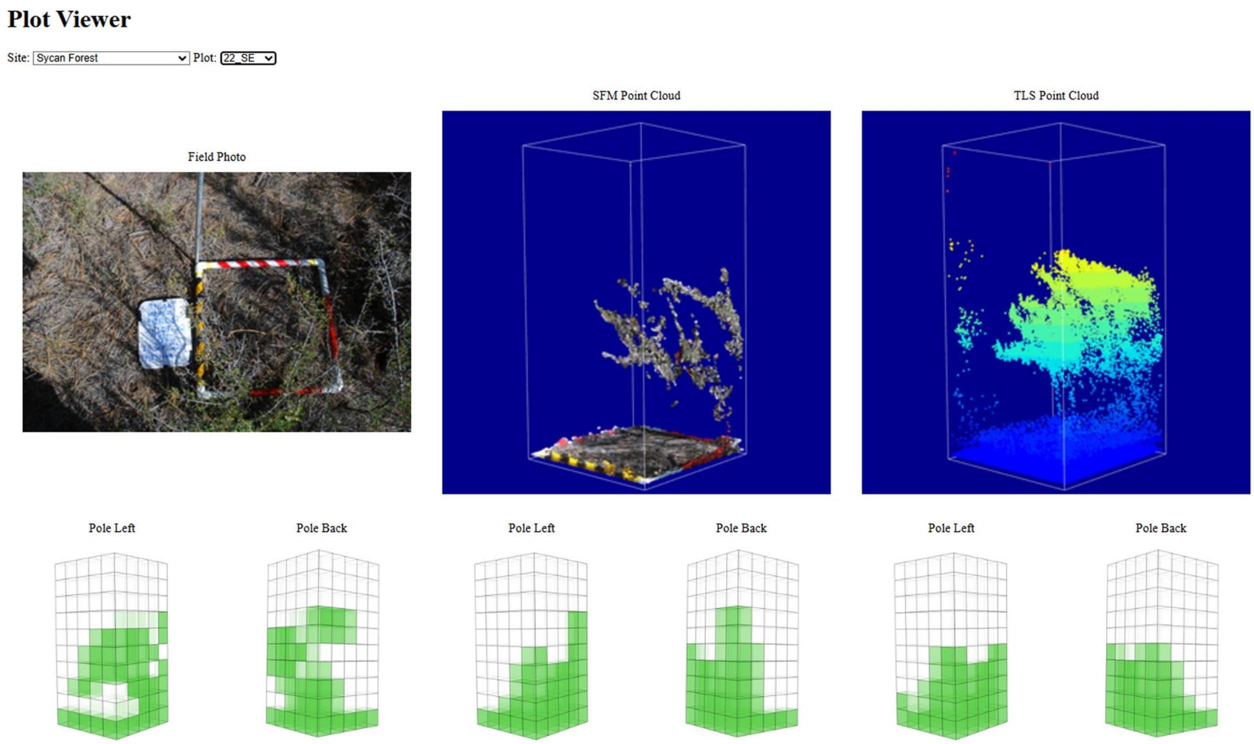

Fig. 6 Image from the 3D Fuels project viewing tool used for quality assurance of TLS and SfM point clouds, comparing plot photos, point cloud visualizations, and voxelized imagery representing each clip plot. Accessible at: https://depts.washington.edu/fft/plotviewer

assure quality and relevance and then loaded the images into Agisoft to create and process point clouds. All point clouds were normalized to heights above ground using the lasground_new function of LAStools. A custom-built R shiny application was constructed for QA/QC to facilitate side-by-side comparisons between clip plot photos, imagery derived from field presence/absence data, and point cloud datasets (Fig. 6).

Biomass processing

Biomass samples were sent to the lab for drying and processing. Biomass collected from the 0–10 strata (including individually sampled voxels) was sorted into component fuel elements (Table 2). Duff samples were sieved to remove soil, then dried and weighed. Soil removed from the samples generally contained some particles of duff that were impossible to separate—these samples were processed according to a detailed protocol (see Prichard et al. 2025). Other vegetation was dried and weighed by strata. Samples were dried at 70 °C for 48 to 72 h depending on fuel density. Forest floor samples of litter and duff collected for bulk density measurements followed similar methods, but litter samples were not sorted and were instead dried and weighed as a single unit. Duff samples were sieved to remove soil, then dried and weighed according to detailed protocols as above.

Each clip plot was assigned a dominant fuel type based on collected field data and plot photos. For plots whose vegetation did not exceed 10 cm in height, dominant fuels were determined using sorted biomass values for each fuel element recorded in the 0–10 stratum. For plots that exceeded 10 cm, where samples were not sorted by fuel element, high-resolution photographs of each clip plot were examined separately by two people for agreement on dominant fuels.

Results

This project produced the 3D Fuels dataset that contains hierarchically scaled data on the structure and composition of canopy and surface fuels across 8 southeastern pine sites, 4 western pine forest sites, and 4 western grassland sites. The data sets are archived within a Wildland Fire Science Initiative data portal (Prichard and Rowell 2026, https://doi.org/10.60594/W4859C), including project metadata, methods documentation and data libraries. The full repository contains all the field and laboratory data collected for this project, organized by site, including ALS, TLS and SfM point clouds, biomass values and presence-absence surveys from destructive sampling plots, and bulk density values from forest floor sampling for each of the sampled sites (Table 3). Raw and processed imagery for each dataset are publicly available

Table 3 3D fuels repository data types, folder names with associated file types and descriptions

Data type	File type	Description
Airborne laser scanning (ALS)		
clipped_area	.laz	ALS tiles merged and clipped to the dimensions of each site
dtm	.dtm	Digital terrain model of site used for normalization
metadata	.laz	Metadata from ALS vendor
tiles	.laz	Non-normalized ALS point clouds covering general area
Terrestrial laser scanning (TLS)		
5×5 plots		
biomass>norm	.laz	Normalized 5×5 m biomass plot point clouds
biomass>scan	.laz	Raw 5×5 biomass plot point clouds
scan_only>norm	.laz	Normalized 5×5 m scan-only plot point clouds
scan_only>scan	.laz	Raw 5×5 scan-only plot point clouds
Clip plots		
clipplot	.laz	Normalized and clipped 0.5×0.5 m biomass clipplot point clouds
dtm	.tif	Digital terrain models of normalized and clipped 0.5×0.5 m biomass clipplot point clouds
Synoptic—entire unit		
scans>clipped	.laz	Normalized registered point clouds of unit-wide 50 m grid point scans; point cloud clipped to site boundary with a 5 m buffer on the exterior of the site extent
scans>clipped_55	.laz	Normalized registered point clouds of unit-wide 50 m grid point scans; point clouds clipped to 55 m distance from scanner
scans>norm	.laz	Normalized registered point clouds of unit-wide 50 m grid point scans
scans>registered	.laz	Point clouds of unit-wide 50 m grid point scans registered to each other
tiles>thinned	.laz	Merged normalized and clipped scans separated into overlapping tiles to cover the entire site; thinned to 1 point per square cm
tiles>tiled	.laz	Merged normalized and clipped scans separated into overlapping tiles (5 m of overlap) to cover the entire site
Field datasets		
bulk_density		Net weight, depths and tree metrics for collected bulk density samples
Clip plots		
biomass	.csv	Biomass recorded at each destructively sampled 0.5×0.5×1 m clipplot
presence_absence	.csv	Presence-absence for each voxel recorded at each destructively sampled 0.5×0.5×1 m clipplot
depths	.csv	Voxel depths (for 5 random voxels per clipplot) recorded at each destructively sampled 0.5×0.5×1 m clipplot
Photogrammetry—close range Structure-from-Motion (SfM)		
images	.txt	Text files made from handheld GoPro videos of plots that were used to create point clouds
norm	.laz	Normalized point clouds made from handheld GoPro videos of plots
video	.mov	Handheld GoPro videos of plots that were used to create point clouds
Photogrammetry—UAS-based digital aerial (DAP)		
5×5 plots		
images	.mov	Raw images of 5×5 plots taken with drone photogrammetry (low altitude)
norm	.laz	Placeholder folder for point clouds of 5×5 plots taken with drone photogrammetry (low altitude)
metadata	.txt	Metadata for UAS flights conducted at site
Synoptic—entire unit		
images	.mov	Raw video of entire site taken with drone photogrammetry (high altitude)
norm	.laz	Placeholder folder for synoptic point clouds taken with drone photogrammetry (high altitude)
Geospatial		
5×5 plots		
biomass	.shp	Shapefiles of 5×5 m biomass plots
scan_only	.shp	Shapefiles of 5×5 m scan-only plots
Clip plots		
clipplot	.shp	Shapefiles of.5×.5 m clip plots
poles	.shp	Shapefiles of plot pole locations
Entire unit		
site_extent	.shp	Shapefile of site boundary and boundary with 5 m buffer

and cross-referenced by site name and geospatial location, including ALS, UAS (not available for all sites) and handheld camera-based SfM photogrammetry, and synoptic and plot-level (both 5×5-m and 0.5×0.5-m) TLS. Field-based measurements include biomass of each voxel plot by vertical stratum in 10-cm increments, and bulk density of duff and litter for each forest floor plot.

Discussion

This study presents an intensively sampled and hierarchically scaled dataset of wildland fuels that can be used to train fine-scale models of relationships between field-based measurement and remote sensing datasets and broader-scale mapping of wildland fuels for operational mapping and fire behavior and effects modeling. Although remote sensing approaches are increasingly available for characterizing forest canopy properties, forest understories are more challenging due to issues of canopy occlusion and the dependency of understories on past management and forest disturbances (e.g., insect outbreaks, windstorms, and wildland fire events) (Loudermilk et al. 2023). Improved sampling approaches for understory fuels are critical variables in wildland fire behavior and smoke modeling, particularly for prescribed fire decision support (Linn et al. 2020; Hiers et al. 2020).

Our study was designed to evaluate and advance methods for 3D fuel characterization and to provide consistently scaled and labeled datasets for model training and evaluation. More specifically, machine learning models can be used to parse 3D point cloud datasets collected from ALS, TLS, and SfM photogrammetry into fuel objects and metrics (Loudermilk et al. 2023; Rowell et al. 2020). Calibration with field plots allows these datasets to be used as the foundation for synthetic fuelbed mapping, starting with fine-scale objects such as individual shrubs or downed wood and scaling to vegetation patches and operational burn units. Statistical relationships developed from this datasets, which will be presented in subsequent studies, can be used to inform probabilistic canopy and understory fuel assignments for wildland fire environments that are common to prescribed burning programs in southeastern and western pine forests (Rowell et al. 2016; Sánchez-López et al. 2026). The field of wildland fuel characterization is rapidly advancing to meet the needs of physics-based fire behavior and effects models (Rowell et al. 2020; Hiers et al. 2020; Loudermilk et al. 2022). Any attempt to measure, model, and map wildland fuels will be challenged with the need for a range of methods and quantification of uncertainty (Keane 2015). While large networks of plots have been sampled to create fuels datasets that span the continental US (e.g., Fuels Inventory Analysis) these relatively coarse 2D datasets are not sufficient to meet the needs of next-generation fire behavior models (Brown and Bevins 1986; Keane et al. 2013).

Summary

This hierarchically scaled dataset contributes to wildland fuels research by integrating state-of-the-art fuel sampling techniques to provide foundational methods and tools for both scientists and managers. At present, methods are still under development to map spatial fuels at scales pertinent to operational wildland fires and for the application of the latest physics-based fire-atmosphere models (Keane 2015). Here, we present combined methods for representing 3D fuels that will provide useful interpretation of remotely sensed datasets to fire and fuels managers for fuels, fire, smoke and atmospheric modeling applications. Specifically, we created a library of 3D point clouds, field data, and processing scripts that partition point cloud data into voxels and create 3D inputs for existing and custom applications. With the expansion of machine learning and artificial intelligence (AI), these fully documented and hierarchically scaled datasets will provide a foundation for parsing imagery to create 3D gridded inputs to next-generation operational models of fire behavior and effects.

Rapid advances are being made in computational fluid dynamics modeling of fire behavior. Because models such as FIRETEC, FDS, and QUIC-fire depend upon gridded, 3D fuels, methods are needed to measure canopy and surface fuels and develop voxelized fuel inputs that represent where fuels are in 3D space and gaps within fuel complexes. Our approach to hierarchical fuels characterization and mapping provides opportunities to develop new metrics for characterizing the inherent heterogeneity of wildland fuels, particularly with respect to fuel reduction treatments and prescribed burning programs. Work with the 3D fuels dataset is ongoing, with (1) development of forest floor biomass models that relate tree crown position to depth, loading and bulk density of litter and duff layers (Prichard et al. 2025), (2) modeled relationships between destructively sampled surface fuel biomass and point cloud metrics derived from TLS and close-range photogrammetry (Nemens et al n.d.. in review), and (3) modeled relationships between overstory crown metrics and understory fuel distributions.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-026-00507-2.

Supplementary Material 1: Table S1: 3D Fuels project UAS photogrammetry data collection: low altitude (5x5m plot-based) flights were conducted only in open forest and grassland sites due to obstructions; high altitude flights were conducted at all sites where UAS-based data collection was permitted. Sites where no UAS data were collected are indicated with ellipses. Table S2: ALS data sources for each field site surveyed as part of the 3D Fuels project field campaign. Fig. S1: Field datasheet used in the 3D Fuels project for ocular presence-absence data and biomass sampling. Example from LANL Forest site, Los Alamos National Laboratory, NM. Fig. S2: Images from the R shiny app tool developed by the 3D Fuels project for clipping 0.5x0.5x1-m plots from larger (5x5m) lidar point clouds. The application uses the high reflectance values of poles and frames used in plot layout to identify clip plot locations (A), poles (B), and 2D frames (C) for sub-setting point clouds

Acknowledgements
We thank Danielle Christianson, Christie Hawley, James Furman, J. Kevin Hiers, Scott Pokwinski and Brett Williams for their foundational work and guidance on this project. We thank our field and laboratory crew members for their hard work and dedication, including Nick Tripodi, Lyndsey Lascheck, Maddy Hallet, Teagan Darmody, Mason Patterson, Henry Gould, Kate Patronik, Grace Swan-Streepy, Jordan Hilton, Sophia Boyd, Jane Wynne, and Caitlyn Bell. Many host agencies supported this research, including the Center for Lands Management (Glacial Heritage and Tenalquot), Florida Forest Service (Blackwater and Tates Hell State Forests), Hitchiti Experimental Forest, Los Alamos National Laboratory, University of Montana (Lubrecht Forest), Suwannee River Water Management District (Aucilla), Tall Timbers Research Station, US Department of Defense (Ft Stewart), US Forest Service (Osceola), and Washington Department of Fish and Wildlife (Methow Wildlife Area). We thank the managers and experts at each of these sites for their support.

Authors' contributions
SJP, ER, JC, and ELL contributed to study design. BB, DN, and PE supported database development and design, DN, CS, JB, BB, GRC, JT, and HR contributed to image processing and data analysis. AH, ELL, RP, and NS contributed to project oversight and collaboration with other SERDP-funded research projects. All authors read and approved the final manuscript.

Funding
This study was funded by the US Department of Defense Strategic and Environmental Research and Development Program (SERDP Projects # RC19-1064 and RC20-1346). This research was supported (in part) by the U.S. Department of Agriculture, Forest Service. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. government.

Data availability
The datasets and analysis scripts for this study are open source and are being archived with the Wildland Fire Science Initiative data repository (https://doi.org/10.60594/W4859C), including project metadata, methods documentation and data libraries (Prichard and Rowell 2026).

Declarations

Ethics approval and consent to participate
N/a.

Consent for publication
N/a.

Competing interests
The authors declare no competing interests.

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Received: 7 March 2026 Accepted: 5 May 2026
Published online: 11 July 2026

References

Brown JK, Bevins CD (1986) Surface fuel loadings and predicted fire behavior for vegetation types in the northern Rocky Mountains

Dickman, L.T., A.K. Jonko, R.R. Linn, et al. 2023. Integrating plant physiology into simulation of fire behavior and effects. *The New Phytologist* 238: 952–970. https://doi.org/10.1111/nph.18770.

Falk, D.A., C. Miller, D. McKenzie, and A.E. Black. 2007. Cross-scale analysis of fire regimes. *Ecosystems* 10: 809–823. https://doi.org/10.1007/s10021-007-9070-7.

Furman, J. 2018. Next generation fire modeling for advanced wildland fire training. *Fire Management Today* 76:48–53.

Hawley, C.M., E.L. Loudermilk, E.M. Rowell, and S. Pokswinski. 2018. A novel approach to fuel biomass sampling for 3D fuel characterization. *MethodsX* 5: 1597–1604. https://doi.org/10.1016/j.mex.2018.11.006.

Hiers, J.K., J.J. O'Brien, R.J. Mitchell, et al. 2009. The wildland fuel cell concept: An approach to characterize fine-scale variation in fuels and fire in frequently burned longleaf pine forests. *International Journal of Wildland Fire* 18: 315. https://doi.org/10.1071/WF08084.

Hiers, J.K., J.J. O'Brien, J.M. Varner, et al. 2020. Prescribed fire science: The case for a refined research agenda. *Fire Ecology* 16: 11, s42408-020-0070–8. https://doi.org/10.1186/s42408-020-0070-8.

Hood, S.M., J.S. Crotteau, and C.C. Cleveland. 2024. Long-term efficacy of fuel reduction and restoration treatments in Northern Rockies dry forests. *Ecological Applications* 34: e2940. https://doi.org/10.1002/eap.2940.

Hudak, A.T., A. Kato, B.C. Bright, et al. 2020. Towards spatially explicit quantification of pre- and postfire fuels and fuel consumption from traditional and point cloud measurements. *Forest Science* 66: 428–442. https://doi.org/10.1093/forsci/fxz085.

Keane, R.E. 2015. *Wildland Fuel Fundamentals and Applications*. Switzerland: Springer International Publishing.

Keane, R.E., J.M. Herynk, C. Toney, et al. 2013. Evaluating the performance and mapping of three fuel classification systems using Forest Inventory and Analysis surface fuel measurements. *Forest Ecology and Management* 305: 248–263. https://doi.org/10.1016/j.foreco.2013.06.001.

Linn, R.R., J. Reisner, J.J. Colman, and J. Winterkamp. 2002. Studying wildfire behavior using FIRETEC. *International Journal of Wildland Fire* 11: 233. https://doi.org/10.1071/WF02007.

Linn, R.R., J. Winterkamp, J.J. Colman, et al. 2005. Modeling interactions between fire and atmosphere in discrete element fuel beds. *International Journal of Wildland Fire* 14: 37. https://doi.org/10.1071/WF04043.

Linn, R.R., S. Goodrick, S. Brambilla, et al. 2020. QUIC-fire: A fast-running simulation tool for prescribed fire planning. *Environmental Modelling & Software* 125: 104616. https://doi.org/10.1016/j.envsoft.2019.104616.

Loudermilk, E.L., J.K. Hiers, J.J. O'Brien, et al. 2009. Ground-based LIDAR: A novel approach to quantify fine-scale fuelbed characteristics. *International Journal of Wildland Fire* 18: 676. https://doi.org/10.1071/WF07138.

Loudermilk, E.L., G.L. Achtemeier, J.J. O'Brien, et al. 2014. High-resolution observations of combustion in heterogeneous surface fuels. *International Journal of Wildland Fire* 23: 1016. https://doi.org/10.1071/WF13160.

Loudermilk, E.L., J.J. O'Brien, S.L. Goodrick, et al. 2022. Vegetation's influence on fire behavior goes beyond just being fuel. *Fire Ecology* 18 (9): s42408-022-00132–9. https://doi.org/10.1186/s42408-022-00132-9.

Loudermilk EL, Pokswinski S, Hawley CM, et al (2023) Terrestrial laser scan metrics predict surface vegetation biomass and consumption in a frequently burned southeastern US ecosystem

Marcozzi, A., L. Wells, R. Parsons, et al. 2025. FastFuels: Advancing wildland fire modeling with high-resolution 3D fuel data and data assimilation. *Environmental Modelling & Software* 183 : 106214.

Mell, W., M. A. Jenkins, J. Gould, and P. Cheney. 2007. A physics-based approach to modelling grassland fires. *International Journal of Wildland Fire* 16:1–22.

Nemens, D, Prichard, SJ, Cova, GR, Drye, B, Eagle, P, Rowell, E and Thoreson J. In review. Quantifying understory fuel structure and biomass using coupled terrestrial lidar scanning, close-range photogrammetry, and field sampling. Fire Ecol.(n.d.)

Parsons, R.A., W.E. Mell, and P. McCauley. 2011. Linking 3D spatial models of fuels and fire: Effects of spatial heterogeneity on fire behavior. *Ecological Modelling* 222: 679–691.

Prichard, S. J., and E. M. Rowell. 2026. 3-Dimensional (3D) Fuels Project: July 2018-February 2024.WFSIData Portal. https://doi.org/10.60594/W4859C.

Prichard, S.J., E.M. Rowell, and A.T. Hudak. 2022. Fuels and consumption (Chapter 2). In *Wildland Fire Smoke in the United States*, ed. D.L. Peterson, S.M. McCaffrey, and T. Patel-Weynand, 11–49. Cham: Springer International Publishing.

Prichard, S. J., D. G. Nemens, M. C. Kennedy, et al. 2025. Forest floor properties in pine forests of the southeastern and western United States. *Fire Ecology* 21:85.
R Core Team (2024) R, A language and environment for statistical computing, R Foundation for Statistical Computing
Ross, C.W., E.L. Loudermilk, J.J. O'Brien, et al. 2024. Lidar-derived estimates of forest structure in response to fire frequency. *Fire Ecology* 20: 44. https://doi.org/10.1186/s42408-024-00279-7.
Rowell, E.M., E.L. Loudermilk, C. Seielstad, and J.J. O'Brien. 2016. Using simulated 3D surface fuelbeds and terrestrial laser scan data to develop inputs to fire behavior models. *Canadian Journal of Remote Sensing* 42: 443–459. https://doi.org/10.1080/07038992.2016.1220827.
Rowell, E.M., E.L. Loudermilk, C. Hawley, et al. 2020. Coupling terrestrial laser scanning with 3D fuel biomass sampling for advancing wildland fuels characterization. *Forest Ecology and Management* 462: 117945. https://doi.org/10.1016/j.foreco.2020.117945.
Sánchez-López, N., A.T. Hudak, M.A. Callaham, et al. 2026. Coupling duff development with tree litter and downed fuel inputs, decomposition and fire consumption in a long-term prescribed fire experiment in Florida. *International Journal of Wildland Fire* 35: WF24205.
Yedinak, K.M., E.K. Strand, J.K. Hiers, and J.M. Varner. 2018. Embracing complexity to advance the science of wildland fire behavior. *Fire* 1: 20. https://doi.org/10.3390/fire1020020.

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