3D Fuels Work Plan

SERDP Project RC19_C1_1064

3D fuel characterization for evaluating physics-based fire behavior, fire effects, and smoke models on US Department of Defense military lands

Project Team:

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Objective

The goal of this project is to advance our understanding of 3D fuel characterization and provide evaluation datasets to advance physics-based fire behavior, smoke and other fire effects models for operational use at scales relevant to Department of Defense (DoD) land managers. Our study is guided by the following research questions:

1) *What are the appropriate sampling resolutions of wildland fuels to model fire behavior and consumption, ranging from full physics-based modeling applications to operational models of fire behavior and consumption?*
2) *What are the critical fuelbeds and physical fuel properties required to advance physics-based fire behavior, smoke, and fire effects models for operational use on DoD installations? Specifically, is fine-scale heterogeneity in surface fuels critical to mapping and quantifying fuel consumption in sites commonly burned on DoD lands?*
3) *How can we most efficiently and accurately create gridded, 3D maps of surface fuel properties based on the integration of remotely sensed imagery and fuel properties informed from field-based and laboratory measurements?*
4) *What are the tradeoffs between input precision, model fidelity, and time to collect and integrate 3D datasets?*

Our overall objective is to characterize the 3D structure and composition of wildland surface that are commonly burned in DoD/DOE prescribed burning programs of the southeastern and western US. Next-generation modeling of fire and vegetation dynamics, fuel treatment decision support, wildland fire behavior and smoke dispersion will rely on computational fluid dynamics models of fire behavior and atmosphere interactions. Gridded, 3D inputs of fuels are required, but to date, effective ways to integrate remote sensing datasets and field data have not been established. We will sample the structural variability of surface fuels at fine spatial scales to inform mapping at larger spatial scales and associated estimates of uncertainty. Sensitivity analysis of physics-based models of fire behavior will be used to evaluate the consequences of coarser grid resolutions on model predictions.

Technical Approach

Based on first-year sampling and work plan development, we have established a hierarchical sampling design and field-tested sampling methods to consistently use across all sites and datasets. From our progress to date, the only uncertainty involves when we can resume fieldwork under COVID-19 restrictions. We will keep in close communication with the SERDP program as the situation unfolds. At present, we are able to dedicate field and laboratory staff to accommodate stay-at-home orders.

Our primary approach of the 3D fuels project is to sample the spatial variation of fuel loading and composition of forests and grasslands using novel destructive harvesting and remote sensing technologies. Specifically, we are employing a hierarchical sampling design for mapping 3D surface and canopy fuels that relies on a combination of airborne and high-resolution terrestrial light detection and ranging (lidar), structure-from-motion photogrammetry (SfM), and ground-based measures of physical fuel properties, including destructive sampling within a 3D grid (termed voxel plot).

We will use these data to produce 3D maps of surface and canopy fuels across a range of spatial scales and vegetation types that function as inputs for physics-based, coupled fire-atmosphere models and other next-generation models reliant on spatially explicit fuels. Additionally, we will use advanced mathematical modeling techniques to develop quantitative models that assign measured properties of fuels, and in the case of highly intermixed fuels (e.g., complex arrangements of surface fuels including shrubs, herbaceous fuels and intermixed live and dead fuel), develop 3D models of functional plant groups to inform mapping assignments.

Application of Research Results

This study contributes to wildland fuels research by integrating state-of-the-art fuel sampling techniques and quantitative fuels modeling with model sensitivity analyses to provide foundational methods and tools for both scientists and managers. At present, methods are still under development to map spatial fuels data at scales pertinent to operational wildland fires and for the application of the latest physics-based fire-atmosphere models (Keane 2015). We are developing new methods and metrics for 3D fuels that will provide useful interpretation of remotely sensed datasets and insights to fire and fuels managers, for fuels, fire, smoke and atmospheric modeling applications. Specifically, our project will produce a 3D library of voxel fuels, intrinsic fuel properties and quantitative modeling scripts that partition point cloud data into voxels and create 3D input for existing and custom applications. This project will evaluate and develop methods that will eventually lead to development of an actual software application that can be used to parse imagery to create 3D gridded inputs to next-generation operational models of fire behavior and effects.

Study Areas

We will characterize 3D fuelbeds for regional fuel types in the southeastern (SE) and western US that are most commonly burned within DoD prescribed burning programs (Table 1). These include:

1) SE longleaf pine (mesic flatwood) understories (4 sites)
2) SE loblolly pine-sweetgum forest understories (4 sites)
3) Western grasslands and grass-dominated pine savannas (4 sites)
4) Western ponderosa pine forest understories (4 sites)

Although geographically distinct and with markedly different climates, the structure of southeastern pine forests and western ponderosa pine forests are often quite similar (e.g., single-story, open forests with grass/shrub/litter understories). Methods that we develop to characterize canopy and understory fuels in these contrasting ecosystems are likely to produce standards that can be broadly applied for mapping applications and to generate 3D fuels inputs for model applications. Specifically, we anticipate that because pine forests have similar structural characteristics, similar scripting algorithms can be used to interpret point-cloud imagery into gridded, 3D representations. Intrinsic fuel properties and fuel moistures can then be tailored to be specific to southeastern and western fuel types.

Within each site, we will identify relatively small blocks (< 2 ha) in fuels that range in biomass and complexity. More specifically, we will select sites to represent a range in understory biomass from low biomass (e.g., a 1-year rough) to high biomass (e.g., 4-5 year rough).

Selection criteria for all sites include available recent airborne lidar scans (ALS), relatively uniform ground surface on gradual slopes (< 30% gradient). Because UAS is necessary for structure-from-motion photogrammetry, we will attempt to use UAS on most sites. UAS restrictions are most likely on DOD/DOE lands. In these instances we will locate sites in vegetation and fuels that are representative of DoD lands but allow the use of UAS. **Table 2** summarizes the wildland vegetation and fuels that will be measured by this study and the relevant sampling methods by fuel type.

Table 1: Candidate study sites. Sites that were completed in year 1 of this project are listed in grey, and planned or potential sites are in white. Sites that allow UAS flights and have recent ALS are listed as yes. Planned coordination with other projects or lead scientists are listed under coordination.

SOUTHEASTERN US SITES					
Site	**Vegetation type (s)**	**UAS?**	**ALS?**	**Sampling date**	**Coordination**
Blackwater SF (FL)	Mesic flatwood wiregrass understory	Yes	Yes	August 2019	FIREX-AQ
Osceola NF (FL)	Mesic flatwood #1 (1 to 2-yr rough)	Yes	Yes	Jan 2020	Rx burn Hoffman project
Tate's Hell SF (FL)	Mesic flatwood / palmetto-gallberry understory 1 yr rough #2	Yes	Yes	Jan 2020	None
Tate's Hell SF (FL)	2-3 yr rough #3	Yes	Yes	Jan 2020	None
Fort Stewart (GA)	Mesic flatwood	Maybe	Yes	Jan 2021	FASMEE Hoffman
Tall Timbers (FL)	Loblolly #1	Yes	Yes	Potential	Hoffman
TBD	Loblolly #2				
TBD	Loblolly #3				
TBD	Loblolly #4				
WESTERN US SITES					
Lubrecht Exp. forest (MT)	Ponderosa #1	Yes	Yes	July 2019	No
Sycan Marsh (south central OR)	Ponderosa #2	Yes	Yes	Sept 2019	Parsons Rx burn
Sycan Marsh	Grassland #1	Yes	Yes	Sept 2019	Parsons Rx burn
Los Alamos National Lab (LANL, NM)	Ponderosa #3	Maybe	Yes	Summer 2020	DOE
LANL	Grassland #2	Maybe	Yes	Summer 2020	DOE
Joint Base Lewis McChord (WA)	Grassland #3	No	Yes	Summer 2020	
Center for Natural Lands Mgmt (western WA)	Grassland #3 (potential proxy for JBLM)	Yes	Yes	Summer 2020	Mell
Spokane Indian Reservation	Ponderosa #4 Grassland #4	Yes	Maybe	Summer 2021	Parsons

Table 2: Descriptions of common canopy, surface fuel and ground fuel categories used for fire and smoke modeling. Fine woody debris (FWD) is a term often used for wood fuel particles $\leq$ 7.6 cm in diameter, and coarse woody debris (CWD) refers to woody fuel particles > 7.6 cm in diameter. Synoptic TLS and SfM are merged images representing the full 200x200 m site.

Fuel Stratum	**Fuel Category**	**Description**	**Sampling methods**
		Canopy fuels	
Canopy	Tree crowns	Fine branches (<6 mm diameter) and dead and live aerial foliage	ALS Synoptic TLS Synoptic SfM
	Snag wood	All burnable portions of dead trees including branches and stem wood	ALS Synoptic TLS Synoptic SfM
	Ladder fuels including vines, branches, tree regeneration	Any fuel that serves as a ladder between surface and canopy fuels	Synoptic TLS Synoptic SfM
		Surface fuels	
Shrub	Shrub crowns and stems	All burnable shrubby biomass with branch diameters less than 5 cm	TLS SfM Close-range SfM Voxel plot sampling
Herb	Grasses and forbs (non-woody vegetation)	All live and dead grass, forb, and fern biomass	TLS, SfM, close-range SfM Voxel plots
Downed wood	1-hr wood (FWD, twigs)	< 0.6 cm (0.25 inch) diameter	TLS, SfM, close-range SfM Voxel plots
	10-hr wood (FWD, branches)	0.6-2.5 cm (0.25-1.0 inch) diameter	TLS, SfM, close-range SfM Voxel plots
	100-hr wood (FWD, branches)	2.5-7.6 cm (1-3 inch) diameter	TLS, SfM, close-range SfM Voxel plots
	1000-hr wood (CWD)	7.6+ cm (3+ inch) diameter	TLS, SfM, close-range SfM
Litter-lichen-moss	Litter	Freshly fallen non-woody material including leaves, cones, pollen cones	TLS, SfM, close-range SfM Voxel plots Forest floor sampling
		Ground fuels	
Organic soil horizons	Oe horizon (upper duff) Lower horizon (lower duff)	Partially decomposed and fully decomposed biomass, including decomposed litter and peat	Voxel plots Forest floor sampling
Basal accumulations		Accumulated organic soil and litter around older trees	Voxel plots Forest floor sampling

Hierarchical Sampling Design

Our hierarchical sampling design incorporates lidar, photogrammetry and field-based measurements to characterize canopy and surface fuels at each study site (**Figure 1**). Recent ALS data are a selection requirement for each site and will be interpreted for canopy and surface fuel characterization (stem map, canopy and surface height models). Paired TLS scans and SfM imagery (where UAS is permitted) are used to cover a 200 x 200 m area. TLS data increases the resolution and accuracy of the stem map and characterize the surface fuels (porosity, surface indices, surface height models). Multispectral SfM imagery, sampled with a UAS, is used to classify and map live and dead vegetation.

For each study site, TLS is sampled along a grid with 50-m spacing to create a synoptic scan (n = 25 points for a 200 x 200m grid). Each scan is collocated with an integrated GPS on the unit. High accuracy GPS locations are collected using RS + GNSS receiver for control points used to geo-locate the UAS imagery. At 18 random locations within the TLS sampling grid, 5x5-m plots are established to capture higher resolution TLS and SfM scans (**Figure 2).** Plots are delineated at each corner with metal conduit stakes with reflective tape that can be detectable in all remotely sensed imagery and used to integrate imagery. TLS scans are taken from the 4 edges of each 5x5 m plot. Low-altitude (< 50m) UAS photogrammetry is taken for each plot as well. Of the 18 scan plots, half (n = 9) are randomly selected for post-scan destructive sampling with voxel plots (see 3D Voxel Sampling). Prior to sampling, close-range photogrammetry is captured across the entire 5x5 m plot with a Go Pro video camera on a long selfie stick with care to minimize trampling of understory vegetation.

Within each 5x5 m plot designated for destructive sampling, five 0.5x0.5 m frames are placed within 1 m of a plot corner and at plot center (**Figure 3**). Destructive plots are labeled as NW, NE, CENTER, SW and SE and are used to develop predictive models of bulk density and biomass. Because most biomass is located in the 0-10cm of fuelbed stratum, and much of that is generally within litter and duff layers, we created an additional forest floor sampling protocol to augment our litter and duff sampling (see Additional Forest Floor Sampling).

Coarse woody debris (CWD) including logs >7.6 cm in diameter and stumps are not adequately sampled by either 5x5 m plot scans or destructive plots. We plan to use synoptic TLS and SfM scans to survey coarse wood and will use a combination of measured and published bulk density values to estimate the biomass of these fuels.

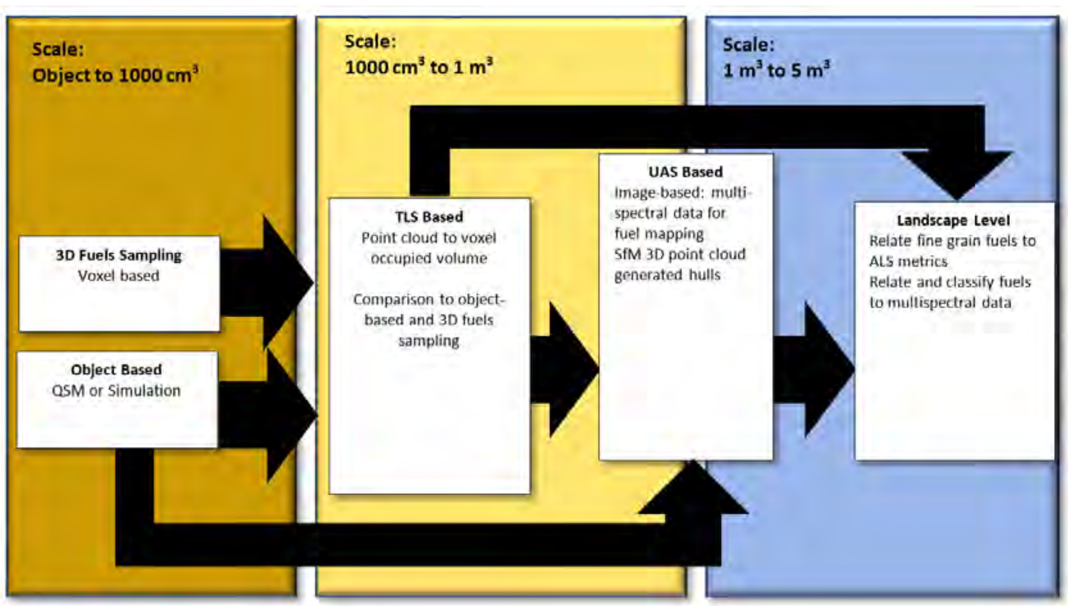

Figure 1: Conceptual diagram of the multi-scaled estimates of 3D fuels characterized using our hierarchical sampling method.

Experimental Burns

Experimental burns will be conducted at a minimum of three sites to collect evaluation datasets of energy release, spatial and temporal patterns of consumption, and assess improvements in consumption estimates from higher-resolution 3D fuels. Spatial heterogeneity in fuel consumption will be estimated by comparing pre- and post-burn fuel loads (e.g. Mueller et al. 2016, Rowell et al. 2016) modeled and mapped at nested scales. Spatially-explicit characterization of consumption, including fuel types that burn mostly in the flaming vs. smoldering phases of combustion, will provide the functional link between fire behavior and fire effects and provide a physical basis from which to measure fire effects and vegetation recovery if burns are coordinated with related studies (Hudak et al. 2020). Consumption mapping will also allow for a greater understanding of the contribution of fuels to wildland fire emissions models.

Our team is actively pursuing opportunities to collaborate with additional research burns. Each site with highly resolved fuels mapping represents an opportunity to conduct prescribed fire research with source characterization of understory fuels and spatial context for fire behavior and effects. Although pre- and post-burn voxel sampling is not possible at each site, we will look for opportunities to have the pre-burn characterization used as context for experimental burns and at least be coupled with post-burn imagery. To date, we have conducted pre- and post-burn sampling at two sites on the Sycan Marsh Preserve (south-central OR) and one site on the Osceola National Forest (northern Florida).

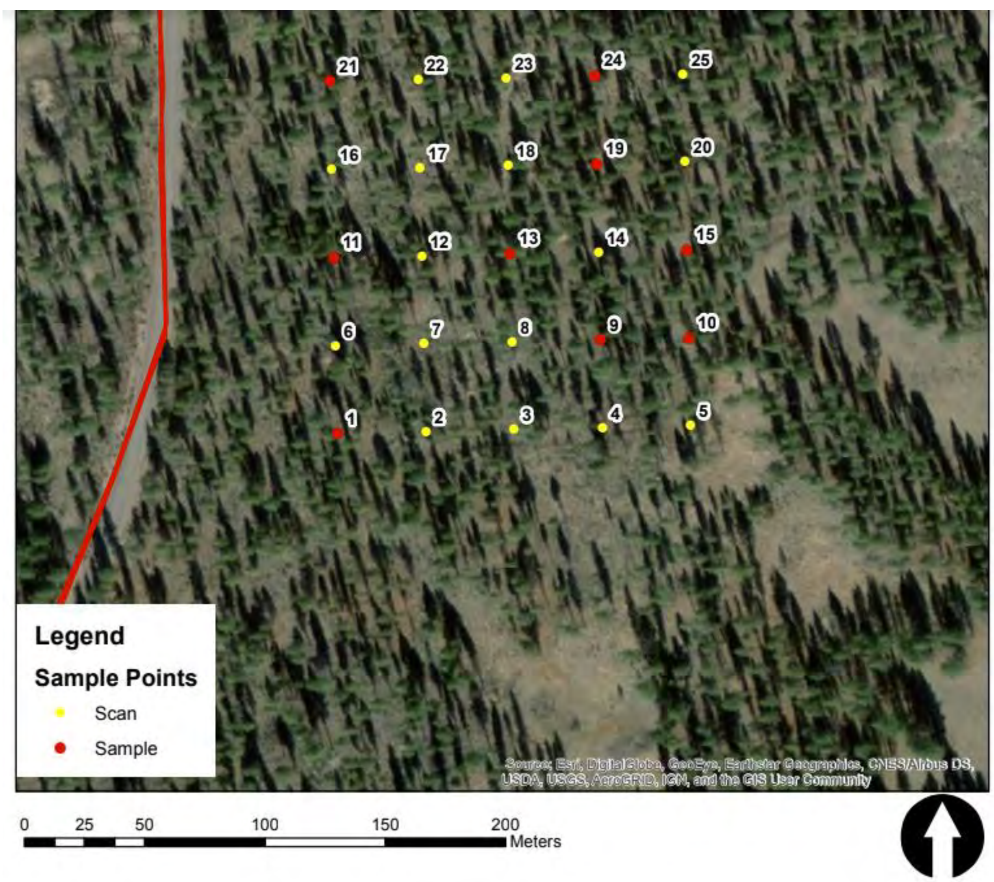

Figure 2: Example TLS scan grid for the Sycan Marsh Preserve pine forest site. Yellow dots represent scan-only plots; red dots represent the nine scan and voxel-sampling plots.

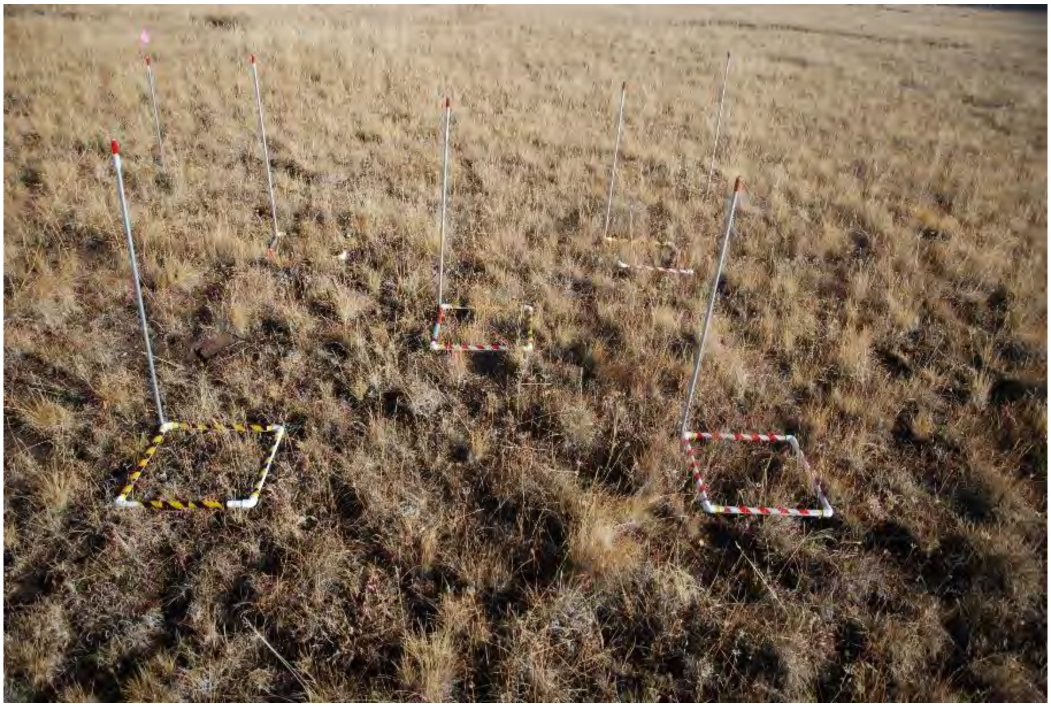

Figure 3: Voxel sampling plot layout within a 5x5 m plot at the Sycan grassland site.

Methods

TLS Point Cloud Acquisition

Terrestrial laser scanning is considered the most stable and consistent platform for localized estimates of fuelbed characterization from fine grain (0.1-0.25 m^2) estimates to larger unit scale characterization (> 400 m^2). The TLS is able to robustly characterize multiple types of fuelbed objects, producing point clouds that represent both the outer hull and a substantial proportion of the internal organization of fuels (Loudermilk et al. 2009). Use of voxel analysis has allowed for estimates of fuel mass in mixed surface fuels of the southeastern US by correlating TLS volume estimates and metrics (e.g., porosity) to field estimates of mass. Preliminary linear models between TLS-based metrics and mass of fine surface fuels including pine needles, fine wood and grass have very high coefficients of determination and are promising for mapping applications in southeastern US forests (Rowell et al. 2020).

We are using both a RIEGL -VZ2000 and RIEGL-VZ400i TLS systems to collect 3D point cloud data at ~5 mm point spacing at 15 m range. The RIEGL is a near-infrared (1050 nm) laser system with a maximum range of 2000 m, which can collect data at rates from 50 kHz to 1 MHz. TLS settings are set to 750 kHz for the laser sampling rate and vertical sampling density of 0.21 degrees. The expected time for the scan is 3m 15s. If the time is significantly greater or less, we adjust the sampling to fall as close to 3m 15s for sampling time. The system is mounted on a tripod at a minimum height of 1.5 m. The REIGL has an integrated L1 GPS receiver, compass and inclination sensors that aid in geo-referencing point clouds.

We organize TLS data acqusition into four types: (1) large scale synoptic coverage that includes a 360 degree scan every 50 m over each site for a total of 25 scan points, (2) a minimum of nine high resolution 5x5m (25m^2) plots with coincident clip plots, (3) a minimum of nine 5x5 m (25 m^2) scan-only plots, and (4) individual shrub scanning. The synoptic TLS data (type 1) provides a frame to apply fuel metrics over a larger unit and to provide improved characterization of the overstory composition and canopy heterogeneity. The first priority of the synoptic scans is to capture the overall site. In instances where a tree would occlude the majority of the site from the flagged scan position, we move the scanner to the closest location to the flagged scan position that will also remove the majority of the occlusion from the tree.

For the 5mx5m subplots (types 2 and 3), TLS data are collected at the four corners of each plot. The laser position is at least 1.5 m from plot corners. The coincident scan and clip plot sites are used to parameterize and validate the models used to estimate fuel metrics. Scan-only sites combined with the coincident scan and clip sites are used to parameterize fuel metric estimates and increase the sample size as we scale to larger domains.

In addition to unit and 5x5 m plot scanning, we are also using TLS scanning of individual shrubs (type 4) to contribute to object-based fuel characterization. For major southeastern shrub species (i.e., palmetto, gallberry), Michelle Bester is coordinating individual TLS scans with destructive sampling to build quantitative structural models (QSMs) of shrubs by species and status. Prior to TLS and SfM scanning, individual shrubs are tagged with reflective tape and labelled. Following scanning, these individual shrubs are destructively sampled for subsequent scanning of leaf on and leaf off plant architecture.

For western shrubs, major shrub species (e.g., bitterbrush, manzanita, Gambel oak) will be sampled as entire plants, scanned individually, and then segmented and weighed by major fractions (stem, fine branch, foliage). Coordinated mass, volume, and TLS sampling of shrubs will facilitate the construction of QSMs of shrubs and synthetic 3D representations of shrub fuels.

Task leads:
Eric Rowell – image acquisition and analysis lead
Michelle Bester – TLS shrub scanning and analysis (PhD student, West Virginia University)
Jonathan Batchelor, University of Washington (PhD student)
Daniel Rosales – TLS image analysis

UAS and Close-range Photogrammetry

Where UAS is permitted, we are conducting high (> 60 m) and low-altitude (< 3 m) scans to generate high-resolution point clouds for detailed and general characterization of fuels within 5m x 5m plots. We are using a UAS-mounted Zenmuse X3 optimal camera and a Micasense Red Edge 3 multispectral sensor to collect photogrammetry scans. The Zenmuse X5 camera captures images using a complementary metal–oxide–semi-conductor sensor with 16M effective pixels and a 4:3 aspect ratio. The shutter speeds range from 8 -1/8000 seconds, the f-stops range from F/1.7 to F/16 and the ISO ranges from 100 – 25600. This allows for high quality imagery collection under varying light conditions and at a reasonably fast flight speed. The camera collects images simultaneously in JPG (compressed) and DNG (raw) format. This camera, coupled with a SD card with a high write speed, allows images to be collected in rapid succession, with large end-lap and side-lap, while covering a relatively large area on a single battery cycle. A large number of images covering an area is necessary when our SfM algorithm creates a 3D model from the 2D images. The Zenmuse X5 enables us to collect high quality, sharp, smear-free images in a timely manner, enabling us to gain the largest benefit from currently available UAS technology. Low and high-resolution UAS data will be collected using this system.

<u>Coarse Resolution UAS Data</u>

High-altitude UAS missions are used to generate unit-wide photo mosaics of the fuelbed at fine grain sizes (>10 cm) to generate fuel classifications of the visible understory and SfM for dominant tree overstory (**Figure 4**). Ground control points are collected as part of the field data collection and are marked with plastic CD's (diameter = 120 mm) covered in bright orange and pink tape. Coordinates are recorded using an RTK/Differential GPS receiver/base combination[1]. Most ground control points (pink CDs) are put precisely at the NW corners of the smaller field plots in order to tie the later close-range drone acquisitions to the 200x200m acquisition.

Flight parameters include an altitude of 100m AGL; with 24 flight lines North-South (NS) and 26 EW to ensure there is ~80% end lap and ~75% side lap for the Micasense, the smaller of the two camera's footprints. Total image count for the X3 is around 1295 files and 2749 for the Micasense. The large disparity can be accounted for due to the footprint of the Micasense being smaller than the X3; several more images are taken due to the Micasense requiring more images to attain 80% end lap. While this accounts for some of the extra images, the vast amount are due to the X3 only taking images with the defined acquisition boundary while the Micasense, due to triggering limitations, takes an image every time the aircraft covers the minimum distance needed to attain the overlap requirements. This also includes vertical movement, as five images are taken during the climb to altitude alone. Travel to starting and ending points all have a breadcrumb trail of images. These images have to be removed or they adversely affect the final output. This is done during the first stages of image processing.

Figure 4: Coarse-resolution UAS photogrammetry scan of Lubrecht Experimental Forest.

<u>High Resolution UAS Photogrammetry</u>

Using methods developed at experiments in Florida and Montana to attain high resolution S*f*M 3D point clouds, we are employing low altitude 8-10 m aboveground) bi-directional UAS data acquisitions that enhance image overlap to produce high-resolution SfM point clouds over each of the nine 5m x5m plots where voxel sampling is planned. Each corner of plot is marked with glyphs, and the pink-tape-covered CD is at the NW corner from the previous synoptic acquisition. For the high-resolution photogrammetry,

[1] Emlid Reach RS X 2; https://emlid.com/reachrs/

we use a Phantom 4 UAS, which collects true-color high-resolution video of each plot. We fly a slow grid (3 flight lines) in each direction (north south; east west) with camera at nadir. The first flight line is on or near the plot boundary, the second in the center, the third on the other boundary (shaped like an S). Then we fly a circular pattern around the plot, keeping the drone about 10 meters from plot center, with the camera 10-20 degrees oblique. The objective is to capture some of the voxel frames (Figure 3) with at least 3 corner targets in some of the frames.

UAS-based SfM point clouds generally characterize the outer hull of the fuelbed. Supplemental occupied volume from TLS and 3D sampling methods will be used to relate hull estimates of surface area with volume and mass to add additional comparative data sets for larger landscape scale estimates of fuel properties. High-resolution imagery will be ~3 mm in resolution to optimize the ability to generate a 3D point cloud.

Task leads:

- *Eric Rowell – image acquisition and analysis lead*
- *Carl Seielstad, University of Montana*
- *Jonathan Batchelor, University of Washington (PhD student)*

Close-Range Photogrammetry

Using an adaptation of methods described in Wallace et al. (2019), we employ a form of photogrammetry that bridges the earlier methods of Bright et al (2016) with the desired outputs commonly expected using UAS-based S*f*M. Using a common GoPro Hero platform, a 1-2 minute video is filmed from a constant elevation and consistent pattern above small plots that are used in 3D voxel sampling at 1080 or 4K resolution(next section). Using bi-directional and highly overlapped image capture from the GoPro video, high-resolution point clouds representing individual plots and the surrounding area (5m x 5m) are generated to assess three-dimensional distributions of fuel metrics that can be related to the robust estimates of fuel metrics from the TLS data (**Figure 5**). This method also can be used to delineate distinct fuel types from the RGB values collected in the imagery, with green wavelengths of passive remotely sensed data representing a variety of live fuels and combinations with low to no green dead fuel properties. This affordable method of fuels collection has the potential to produce large numbers of samples over increasingly larger areas that can be used to train coarser grainsize TLS, UAS, ALS, or NAIP imagery for unit and landscape scale estimates of critical fuel properties.

Task leads:

- *Eric Rowell – image acquisition and analysis lead*
- *Gina Cova – UW Master's student*
- *Susan Prichard and Van Kane (UW) – project advisors*

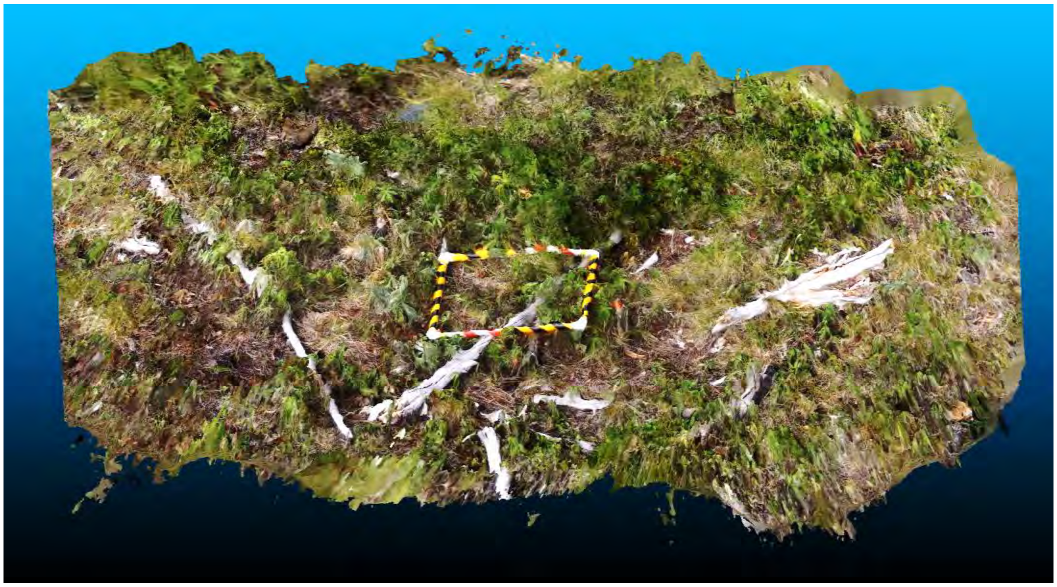
Figure 5: Close-range photogrammetry scan with a voxel plot frame, Lubrecht Experimental Forest.

Image processing

We are using Agisoft Photoscan image processing software configured and tested for multi-thread/processor computing to generate ortho-photomosaics and SfM-based 3D point clouds. We also leverage the RGB imagery to segment live and dead fractions of the fuelbed to inform separation by voxel. Based on synoptic SfM and TLS imagery, we will classify understory fuels into major vegetation/fuel types to inform unit-level mapping. Raw and integrated imagery will be stored and served to the public at the USDA Research Data Archive. Final image datasets (synoptic TLS, photogrammetry, and close-range photogrammetry) will be housed in a central repository managed by Ben Bright (3D Fuels Data Manager).

Task leads:

- *Eric Rowell – image acquisition and analysis lead*
- *Carl Seiestadt – SfM photogrammetry*
- *Brian Drye – UW software engineer, image processing for close-range photogrammetry*
- *Gina Cova – close-range SfM analysis*

3D Voxel Sampling

Samples from all consumable fractions of live and dead fuels are collected in 3D sample plots and analyzed in the laboratory to build a library of surface fuel properties including bulk density by vegetation and fuel type. For shrub and tree species with complex architecture, foliage and branch samples are collected and individually scanned with TLS, facilitating 3D modelling of shrubs, trees and other plants as coherent geometric structures (Parsons et al. 2011). The 3D sample plot dimensions are 0.5 m on each side in x and y, and 1-2 m in z., segmented into 10-cm vertical strata (Hawley et al. 2018).

Although thermally thin (≤ 10 mm) fuels are the primary driver of physics-based fire behavior models, we also sample thermally thick (> 10 mm) fuels as downed wood, litter and duff. Fine wood biomass, litter and duff are collected as part of the 3D fuels sampling framework. Litter and duff are separated in the field and bagged. Samples by fuel type and size fraction are oven dried at 70°C for 48 hours and then weighed for dry weight biomass.

Coarse wood is included in voxel plots, but the sample area and frequency are insufficient to adequately characterize logs and stumps. These fuel types will be mapped and quantified using a combination of synoptic TLS and high-altitude SfM scans.

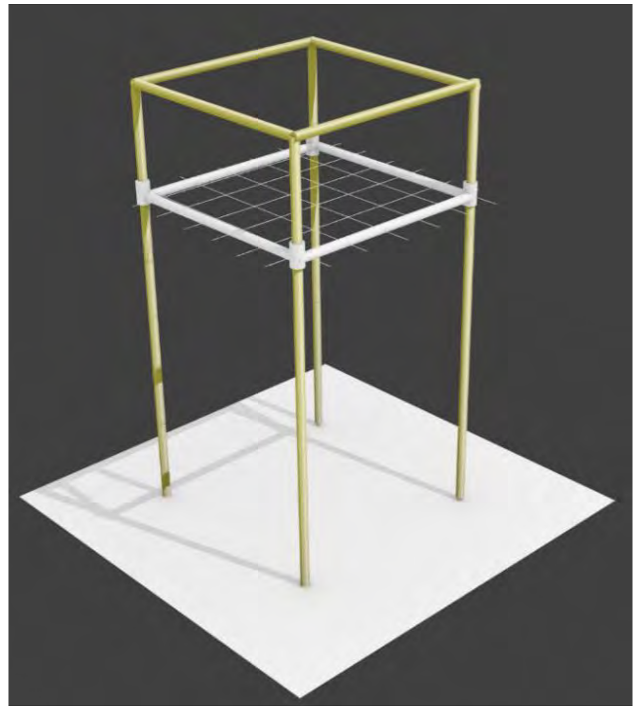

Figure 6: 3D voxel sampling grid. Fuels are sampled in 10 cm layers, starting at the top of the fuelbed and working down to the last 10 cm (Hawley et al. 2018).

<u>Sampling Methods</u>

The 3D field fuels sampling follows the methodology initiated by Hawley et al. (2018). With sliding square set at the 90-100 cm height, the 3-D frame (**Figure 6**) is centered and orientated so the first voxel of each stratum is located in the northwest corner of the plot. Metal wires are inserted to establish a 10x10x10-cm grid for each 10x50x50-cm stratum. Sampling proceeds from top to bottom within each plot (**Figure 7**). Voxels are read north to south and west to east with the lowest voxel number located in the northwest corner. The metal rods outline the voxels and are the floor of the stratum. The voxels are also viewed from the side, as it was easier to note fallen litter such as pine needles. If vegetation measured in the voxel plots extends above 1 m in height, biomass of the fraction above 1 meter is noted on a data sheet, clipped, and bagged, but the voxel sampling methodology is not applied above 1 m. From 100 cm, the larger square is lowered to the highest stratum that contains biomass. If a stratum does not contain biomass, it is noted on the data sheet. While lowering the larger square, the metal wires are removed as needed to preserve the location of the vegetation at the stratum. After lowering is complete, the metal wires are threaded through the drill holes and vegetation to again outline the location of the voxels.

On the data sheet, the present or absent (binary data) of the different fuel class types is noted for each voxels (**Figure 8**). A voxel can have multiple fuel types. If only trace amounts of fuels exist within a voxel, the voxel cube is marked as empty. For each stratum above 0-10 cm, the entire stratum is clipped and bagged. Following destructive sampling, the larger square is lowered 10 cm to the next height stratum; again removing and threading metal rods as needed to work around vegetation. The voxel sampling and biomass collection is repeated (**Figure 9**).

For the 0-10 cm stratum, a total of five 10x10x10-cm (1000 cm^3) voxels are sampled based on predetermined random sampling using a random number generator. Biomass is clipped and bagged from randomly selected voxels. Biomass samples are sorted into separate bags for duff, standing dead stems, and litter/understory vegetation. After biomass is removed from the random voxels, the remaining biomass of the 0-10 cm stratum is clipped and bagged.

At the 0-10 cm height stratum, biomass is harvested to the top of the soil profile. Stems are harvested as close to the soil as possible. Where voxel plots contain CWD (i.e. large logs or stumps), the material that falls within the plot is collected with a hand saw or chainsaw. Where duff is present, the total depth of the lowest stratum is > 10 cm. In these instances, depth is taken at the 5 randomly sampled voxels and averaged for a stratum depth.

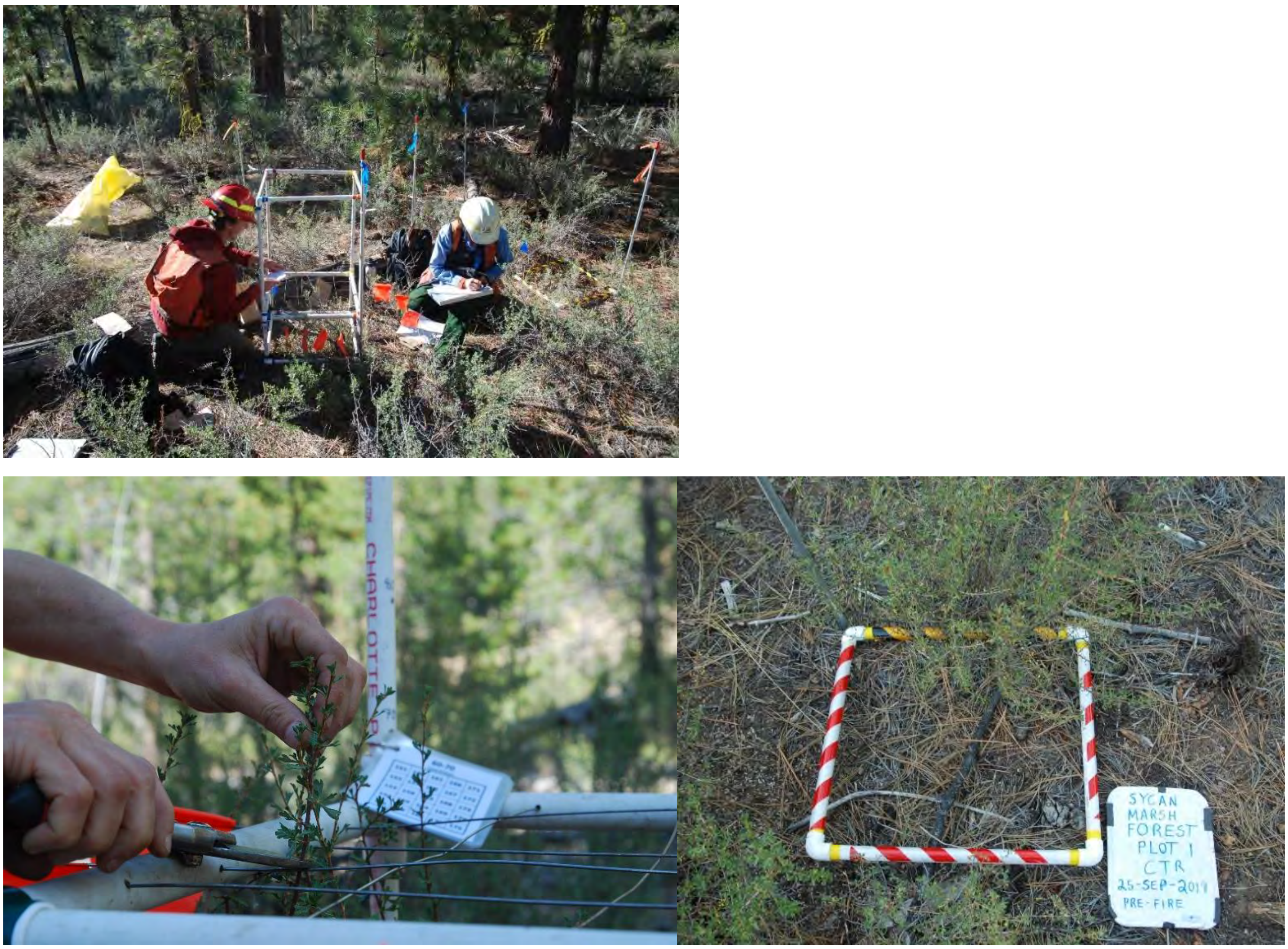

Figure 7: Voxel sampling of a forest understory plot at the Sycan Forest site.

Voxel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	Height:
Woody live shrubs/trees (D,E,OD,OE,OM,EM,DM,M)																										0-10 cm
Woody leaves/litter (D,E,OD,OE,OM,EM,DM,M)																										
Woody standing dead shrubs/trees including conifers																										
Conifer live seedling/saplings																										
Vines (and vine litter)																										
Wiregrass/bunchgrass (W,B, WB)																										
Other graminoids																										
Forbs (and forb litter)																										
1-hr fuel																										
10-hr fuel																										
100-hr fuel																										
1000-hr+ fuel																										
Pine cone																										
Conifer litter (bark flakes, pollen cones, other needles)																										
Pine needles (L, S, LS)																										
Other (state)																										
Other (state)																										
Empty voxel																										
Notes																										

Figure 8: Sample 3D voxel form for the 0-10 cm stratum.

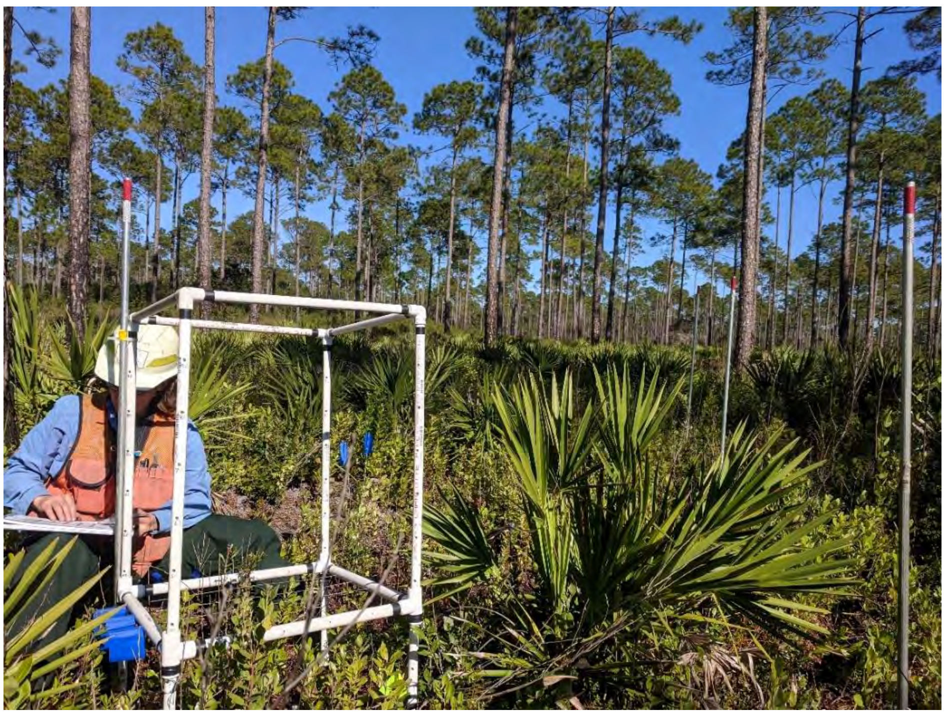

Figure 9: Voxel plot sampling in a forest understory plot at Tate's Hell SF (Site A).

<u>Dry-weight biomass</u>

The collected aboveground biomass samples are dried and weighed at the Pacific Wildland Fire Sciences Laboratory in Seattle, WA as well as the USDA Forest Service, Southern Research Station, Athens Fire Lab in Athens, GA. Samples are dried in ovens at 70°C until a stable weight is achieved. Most biomass samples require 48 hours of drying time, but coarser fuels such as wood particles >7.6 cm generally require 72 to 96 hours. Once dry, the weight (g) is recorded.

<u>Sorting by fuel element</u>

Samples are sorted into categories based on fuel element (foliage, woody stems, pinecones, etc.), diameter class, and live dead status. Litter and live plant samples are sorted into fuel element types and live and dead components for live plants. Subsamples of fine time lag (1-hr) live woody fuels will be further divided into 5 size classes of fuel elements: foliage, very fine twigs (diameter < 3 mm), fine twigs (3-6 mm), medium twigs (6-10 mm), large twigs (> 10 mm).

Task leads:

- *Jim Cronan and Deborah Nemens – FERA crew and laboratory analysis leads*
- *Susan Prichard and Eric Rowell – data analysis*
- *Maureen Kennedy – power analysis and study design*

Figure 10: Photo of 0-10 cm stratum at the Sycan Forest site following sampling of the five randomly-sampled 10x10x10-cm voxels.

Additional Forest Floor Sampling

For forest sites with accumulated litter and duff (termed the forest floor), we are conducting additional sampling to increase our sample size of these fuel types. Using bulk density sampling squares (0.25 x 0.25 m), we will augment the 3D voxel plots with additional plots that sample litter and duff layers where present on SE and western pine forests. To evaluate if forest floor distributions can be modeled relative to tree crowns, we are establishing a minimum of 18 transects radiating from the edge of randomly selected trees to outside the projected crown to facilitate development of models that predict forest floor biomass using tree stem and crown mapping. A minimum of 9 trees for forest sites will be randomly selected for a given number of trees around each terrestrial lidar scan plot.

To select a tree, we randomly set an azimuth and then locate the first tree that meets criteria moving in a clockwise direction from the azimuth. Trees must be at least 15 cm DBH, distance to the tree drip line must be at least 15 m from the lidar plot center (to avoid disturbance to forest floor from foot traffic during lidar plot data collection), and no more than 30 m from the lidar plot center (**Figure 11)**. Once a tree is located it is tagged, photographed, and GPS coordinates should be collected.

Bulk density samples are collected along two transects originating from the bole of the tree and extending north and south with three sample locations per transect. Samples locations are 10 cm from base of the bole, half the distance between the bole and drip line of the crown, and 2 m from the edge of the nearest drip line (**Figure 12**). If the forest has a closed canopy, the third sample is collected 2 m from the drip line of the tree being sampled. In all cases, we note if the canopy is open or closed above each sample.

Prior to destructive sampling of forest floor layers, the square is cleared of live and dead shrubs and grasses, tree cones and downed wood, leaving litter and duff layers remaining. Downed wood, pine cones, etc. are considered part of the forest floor when the central axis of the material lays below the litter/duff boundary. Litter that is suspended in grass or other surface materials is not considered part of the forest floor and is excluded from the bulk density sample. A bulk density sampling square is placed on the top of the forest floor, and material along the edges of the frame is carefully clipped to allow the frame to be inserted to the base of the organic soil layer (duff). Once the frame is in place, six pins (nails or welding rods) are equally spaced on a systematic grid such that the top of the pin is flush with the litter. If an obstruction such as a rock or root prevents this, we note the distance between the top of the pin and the surface of the litter layer.

For each pin, we record the depth of the litter layer to the nearest mm. Once depths have been recorded, the litter layer is carefully collected and stored in a paper bag. Pins are then pushed further into the soil so that the top of each pin is flush with the duff layer. We then record the depth of the duff layer at each pin location and collect the sample into a paper bag.

Task leads:

- *Jim Cronan – FERA crew lead*
- *Susan Prichard & Maureen Kennedy – power analysis and study design*

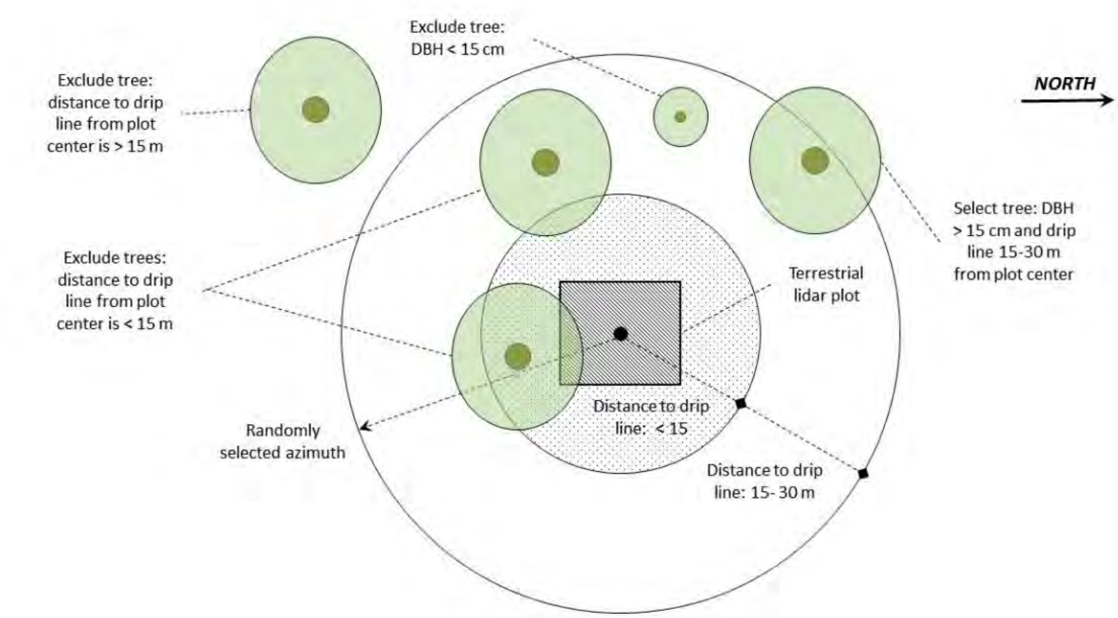

Figure 11: Tree selection for forest bulk density sampling. Trees are selected at each site by randomly selecting an azimuth at each 5x5 m scan plot and selecting the first tree that meets our criteria (> 15 cm dbh with a distance from plot center to drip line between 15 and 30 m).

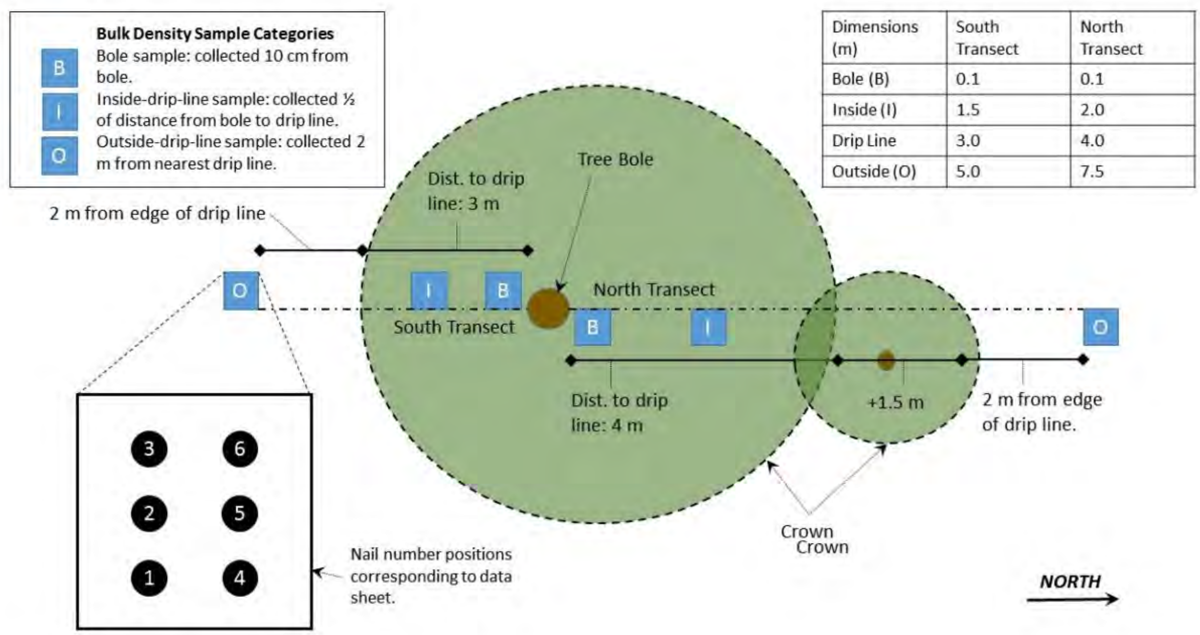

Figure 12: Plot layout for forest floor bulk density sampling. Samples are collected from 3 locations along two transects running to the N and S of sample trees.

Intrinsic Fuel Properties

A fuel properties database and online library is being developed to house published and measured values for fuels at the object (e.g., shrub or litter layers) and element (e.g., grass blades or pine needles) scales. Values will be used to parameterize fields in 3D fuel models with computational inputs to computational fluid dynamics (CFD) models that cannot be measured remotely. We also will develop quantitative models (See Object-based Fuel Characterization section) that relate remotely sensed attributes with fuel properties. These relationships can then be used to impute these values to 3D fuelbeds at the relevant scale of the model. Physical fuel properties required as inputs for CFD fire behavior models (Linn et al. 2002, Mell et al. 2007) will be compiled (**Table 3**).

The intrinsic fuel properties library will include published values and field samples from our 3D fuels sites. We will first conduct a literature review on relevant fuel data for each variable. We will then supplement the database with measurements taken from collected field samples in representative SE and western sites as part of the 3D fuels field campaigns. Fuel property samples will be collected from a subset of randomly selected 1000 cm^3 voxels in 3D voxel plots. This subset will be part of the same subset of voxels destructively sampled to determine bulk density and fuel load. Embedding the fuel property sampling protocol with the 3D sample plots will reduce redundancy of the sampling effort and provide a dataset of fuel properties with high model sensitivity at a comparable resolution to fine-scale TLS fuel characterization. Sample size will be calculated based on prospective power analysis (beta = 0.1) of data from previous published values or pilot studies.

Variables with high model sensitivity include bulk density, surface area to volume ratio, fuel moisture, and particle density. Variables with low model sensitivity that will mostly be derived from published values include specific heat, heat of combustion, char fraction, and ash fraction. Fuel moisture will be measured for experimental burns, but we will not develop a library for this variable. Fuel moisture, especially for thermally thin fuels, is consistently in flux due to changing environmental conditions and must be modeled at fine temporal scales for fire models.

The FERA team visited the Missoula Fire Sciences laboratory in November 2019 and worked with Matt Jolly's team on intrinsic fuel property measurements, including heat of combustion and surface area to volume ratio. When our field and laboratory technicians are allowed to travel and visit other labs, we plan to schedule additional visits to the Missoula Fire Sciences laboratory and conduct measurements on 3D fuels samples.

Table 3: Intrinsic fuel property library field definitions.

Fuel property	Unit	Definition
Ash fraction	Proportion	Fraction of completely consumed fuel that is ash, reflecting mineral content
Bulk density	g/cm3	Mass per volume of vegetation or fuel, including interstitial air space (e.g., bulk density of in-situ litter or duff) (g/cm^3)
Char fraction	Proportion	Remaining mass of a fuel particle after incomplete combustion (black ash)
Fuel moisture content	Percent	Fuel moisture content (%) expressed as the percentage of fuel that is water, measured by taking the gross weight minus the dry weight of fuel
Heat of combustion	MJ/kg	The amount of heat released from a known mass of a substance during combustion
Packing ratio	Proportion	The fraction of a known volume occupied by fuel particles -- calculated as the bulk density divided by the particle density
Particle density	Mg/mm3	Mass per volume of fuel element (leaf, fine branch, stem) (mg/mm^3)
Specific heat	kJ/g	The amount of heat (kJ) required to raise the temperature of the mass of a given substance by unit temperature (C)
Surface Area to Volume Ratio (S:V)	cm2/cm3	Ratio of surface area to volume (cm^2/cm^3)

Sampling methods:

<u>Bulk density</u>

Bulk density will be determined for live fuels by determining the dry weight of fuel elements in randomly selected subset of voxels within 3D fuel plots. Live samples will be sorted according to fuel element categories, dried, and stored according the same requirements for SA:V samples. Litter and duff bulk density will be sampled from the base of 3D fuel sampling plots and additional forest floor bulk density plots. All bulk density samples will be weighed with a 0.001 accuracy digital balance.

<u>Combustion properties</u>

Heat of combustion, specific heat, char fraction, and ash fraction are each combustion properties that describe the extent of energy decomposition during different phases of combustion relative to a given mass of a fuel particle. For biomass components where published values for similar fuels are not available, a minimum of 20 samples will be collected from objects or sub-plots. Staff will process samples and measure combustion properties by bomb calorimetry (Susott et al. 1975).

<u>Surface area to volume ratio</u>

Surface area to volume ratio (SA:V) measures the ratio of the surface area of a fuel particle to its volume. Thermally thin fuels such as tree needles or grasses have SA:V and can respond to ambient temperatures and relative humidity. In contrast, fuel elements such as large logs have low SA:V. We are working with Matt Jolly and Elliott Conrad at the Missoula Fire Sciences Laboratory to develop measurements for SA:V for common live and dead surface fuels for 3D fuel characterization.

Fuel moisture content
For experimental prescribed burns, day-of-burn fuel moisture samples will be collected for each thermally thin fuel element defined for the study site. A minimum of twenty 10 g samples will be collected systematically along the periphery of each 3D fuel-sampling plot. Sample weight will be kept low to reduce water loss during collection. Samples will be stored at 10 °C in puncture-resistant hard containers with screw-on lids and transported to facility where wet weight will be recorded with 0.001 g accuracy calibrated scales mounted to a permanent surface. Wet weights will be recorded within 6 hours of sample collection. Onsite mobile weather stations will provide relevant weather data (temperature, relative humidity, and 2-m wind speed and direction) for at least one month prior to the day-of-burn that can be correlated with fuel moisture samples. Recording resolution will be hourly for the month preceding the burn and every minute for the day of burn.

Particle density
Particle density is the mass of material for a given volume and is expressed as mg mm^{-3}. This variable is an input for biometric equations to calculate weight because density varies across species and vegetative structures. Particle density is also necessary to calculate the packing ratio, a critical input variable for fire behavior models. For biomass components where particle density is unknown, a minimum of 20 samples will be collected from the 3D fuel plots. Particle density samples will represent a single object or sub-plot depending on the fuel object. Collection and storage techniques will follow procedures described in Cornelissen et al. (2003). Mass measurement procedures will follow oven-dry methods described in the fuel moisture content section except a 0.0001 g accuracy analytical balance will be used to weigh samples.

Task leads:

- *Jim Cronan and Deborah Nemens – laboratory analysis leads (FERA)*
- *Susan Prichard – lead for database development (FERA - UW)*
- *Paige Eagle – database development (FERA - UW)*
- *Matt Jolly and Elliot Conrad – collaborators (Missoula Fire Lab)*
- *Anne Andreu – literature review (FERA - UW)*

Object-Based Fuel Characterization

Fuel can be distilled down to individual objects that comprise elements within a fuelbed (Hiers et al. 2009, Keane 2015). Individually, these objects each occupy a specific volume and often have different fuel properties, such as bulk density, varying with fuel type. In CFD models such as FIRETEC and WFDS, objects are often aggregated to represent total fuels and bulk density for a discrete volume (e.g. voxel grid cell). However, representing these objects as discrete entities can be accomplished by maintaining the spatial details of their 3D structure as a virtual wire frame or mesh and allows more in-depth consideration of the role of these fuels within a CFD model. For example, drag forces, radiative and convective heat transfer and convective cooling can be explored, often with smaller simulation domains and more detailed simulations. In general, computational constraints prohibit model simulations that account for the individual architecture of each leaf on a branch, but the capacity to represent finer detail is important for robust examination of how to best aggregate fuels and still maintain model performance. We will use multiple approaches for object-based fuels characterization:

1) *High-resolution simulations*, in which individual fuel vegetation types (e.g. grasses, leaf litter, coarse

woody debris) or objects will be described as three dimensional meshes that have a specific surface area and fuel mass that can be predicted as a function of unit mass per unit of surface area (g cm^{-2}). These simulations can be assembled into mixed representative fuelbeds and distilled to estimate bulk density and mass per unit volume (g cm^{-3}).

2) *Quantitative structural modeling* (QSM) is an analytical technique that distills point clouds with mathematical models that systematically and iteratively filter and fit various shapes to the objects present in a point cloud, thereby accounting for the incomplete nature of LiDAR scans due to occlusion and point densities. There is a developing body of literature exploring QSM in several realms of inquiry with the study of trees and biomass being most relevant to this work. For example, Calders et al. (2015) compared QSM-derived models of biomass from numerous large trees with destructively harvested measurements and found their models to be highly accurate. Much of the current work on QSM model development is provided as open-source, presenting us with a well-developed starting point. Michelle Bester and Nick Skowronski are leading a QSM modeling task for southeastern US shrubs for this project.

3) The third method is segmentation and classification of surface and canopy fuel strata using combinations of point cloud metrics and UAS digital imagery. Point cloud objects and fuels characterization uses a new prototype algorithm to separate points into four fundamental categories and assignment of mass and volume (Cabo et al. 2018). Discrete surface fuel objects are detected using object-based image analysis for digital imagery that when tied with 3D object volumes provides detailed information regarding distributions of fuel type, dead\live ratio, and course woody distributions. Embedding the physical fuel property variables measured in the collocated 3D sample plots will preclude the need for additional sampling effort to characterize larger 3D objects; it is also impractical to destructively sample entire trees or shrub clumps.

The physical fuels properties for the respective fuel components (tree stems, branches, needles, shrubs, herbaceous) will be assigned to the 3D objects for those corresponding fuel components. For example, the estimated volume of a given object (e.g., shrub clump) can be multiplied by a known bulk density to calculate biomass. The type of fuel object (i.e., tree stems, branches, needles, shrubs, herbaceous) will be classified from the point cloud after Cabo et al. (2018), and the fuel properties imputed from the 3D reference library (FCCS) to populate the objects in the scene with physical fuel properties needed to estimate fire behavior and emissions. This approach will be further expanded on in the object-based aggregation of fuel structures in another SERDP project (RC20-C3-1346, Hudak PI).

Task leads:

- *Silva: ALS interpretation*
- *Bester and Skowronski: QSM shrub/small tree models*
- *Rowell and Loudermilk: TLS-derived indices*
- *Cova (UW Masters Student): close-range photogrammetry*
- *Rowell - synthetic fuelbed elements*

Canopy characterization

Computational fluid dynamics models are sensitive to distribution and density of individual tree placement on the landscape. To detect individual trees, we will apply tree-detection algorithms for stem mapping and crown characterization to available ALS imagery (Silva et al. 2016, Roussel et al, 2020). Two software programs, TREES and STANDFIRE, can be used to ingest stem map data into CFD models. TREES uses a tree list with attributes of DBH, tree height, crown width, and height to crown base that are then converted to irregular mesh parabolic shapes (Parsons et al. 2011). STANDFIRE integrates the Forest

Vegetation Simulator and assumes probabilistic distributions of trees by species. The same canopy metrics are used to attribute the tree objects, though STANDFIRE uses the logic and allometric equations that allow for distribution of fuel mass in the canopy proportioned by fuel class (needle, branch, and stem). These proportions can be informed by the fuel type classification of Cabo et al. (2018).

Several stem detection algorithms exist based on the lidar derived canopy height model (Silva et al. 2016) and 3-D point cloud (Li et al. 2012) and allow for segmentation of the tree crown into distinct objects (Roussel, 2020). Using these remotely sensed stems, we can use existing methods to develop canopy inputs for CFD modeling (e.g., Silva et al. 2018). However, these generalized trees are a functional impediment to detailed or realistic fluid flow through canopies that affect fire propagation through surface fuels or transition into canopy driven fire (**Figure 13**). Therefore, we will leverage the substantial amount of data derived from the TLS that can produce thousands of detailed models of bulk density distributions for numerous species. To scale TLS-based metrics to larger units, we will use object-based canopy characterization to map canopy biomass and other properties by estimating parameters from an ALS stem detection map.

Task leads:

- *Andy Hudak and Carlos Silva – canopy and crown characterization*
- *Eric Rowell and Tall Timbers – image analysis*

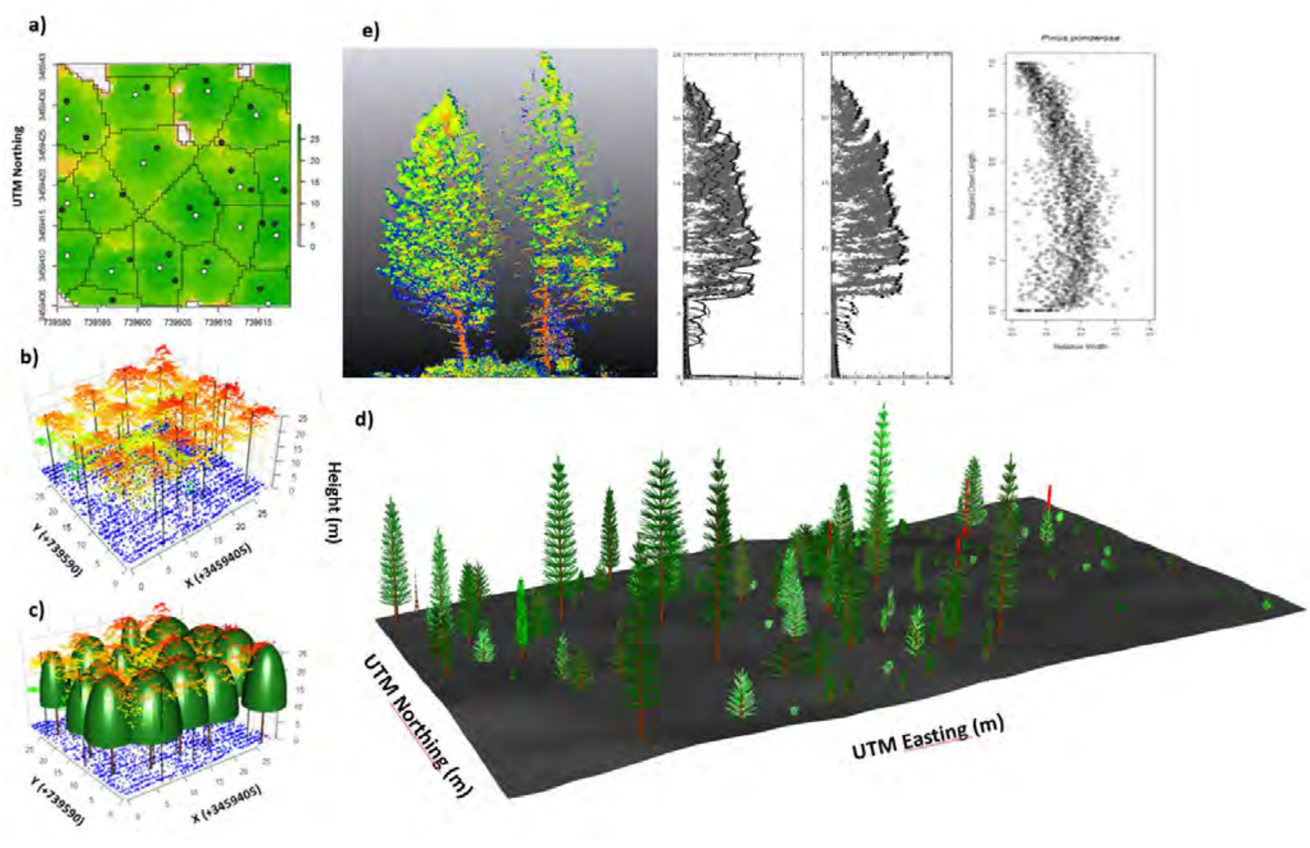

Figure 13: Comparison of airborne lidar (ALS) based crown mapping (a-d) and generic tree representations (e) to a) ALS-derived canopy height model and field (black) and trees detected (white); b) ALS-point cloud and field trees; and ALS-derived single tree representation in 3D as solid (c) or conifers (d) shapes.

Shrub characterization
Shrub fuels are often an important component of wildland fuel biomass, contributing to fire intensity and spread depending on their fuel moisture and intrinsic fuel properties. Seasonal dynamics in fuel moisture influence if and when shrubs are readily consumed in a wildland fire event. Functional traits such as shape, branching pattern and vertical and horizontal distribution of fuels affect permeability and influence the flammability of shrubs. Much like trees, individual shrubs or clusters of shrubs are distinct objects that influence wind flow, fire intensity and fire spread. We will use a hierarchical sampling approach to characterize shrub objects including synoptic TLS and SfM scans to define shrub objects, close-range photogrammetry and individual TLS scans to characterize shrub architecture and destructive sampling of shrubs to determine fuel properties including bulk density and surface area to volume ratios.

Many of the advancements in canopy characterization can be used to define shrub objects, including stem-detection algorithms that can be adapted to detect tall shrubs within TLS imagery. Michelle Bester, PhD student at West Virginia University is working with co-I Nick Skowronski to develop quantitative structural models (QSM) of shrub architecture and physical properties for major shrubs within our southeastern forest sites. Her initial fieldwork included integrated sampling with the 3D fuels project at Tate's Hell State Forest in which she tagged replicated gallberry, saw palmetto and other common shrubs within 3D fuels scan plots. Field measurements were conducted in which she measured shrub properties such as height to live crown, diameter at breast height and approximate height and widths. Additionally, whole plants were harvested and additional TLS-scanning of plant and branch architecture both leaf-on and leaf-off was coordinated with volume and dry weight mass measurements. These measurements will be used to create, optimize and verify the QSM (**Figure 14**). A similar sampling approach of major western shrub species will also be conducted in order to inform object-based fuel characterization of shrub objects at all 3D fuel sites. Validation will be conducted both qualitatively through visual inspection as well as quantitatively through regression analysis.

Task leads:

- *Michelle Bester - southeastern shrub TLS image analysis and QSM modeling (dissertation work)*
- *Nick Skowronski – project advisor for southeastern shrub modeling*
- *Tall Timbers TLS Crew – individual scanning of major western shrub species*

Other fuels
Coarse wood, including logs, stumps and piles, are readily detected from TLS and SfM photogrammetry and can be characterized as distinct objects through a combination of geometric pattern recognition, color and TLS texture indices. Through coordinated field observation, decay class and species assignments may be possible to refine estimated wood density and mass calculations.

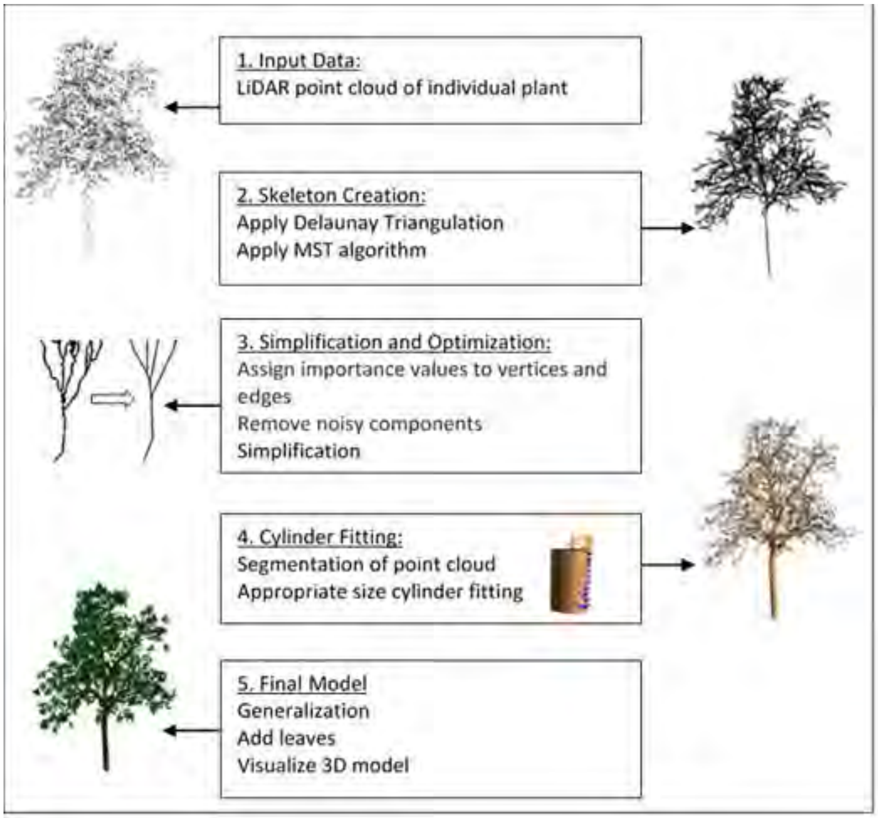

Figure 14: Overview of quantitative structural modeling approach to shrub characterization.

New Metrics

Effective fuels management requires metrics that describe fuels in terms useful to managers. Before CFD models become operational, fire and fuels managers require interim metrics that translate lidar and other remotely sensed datasets to practical fuels management questions. At present, managers often use torching and crowning indices to evaluate crown fire potential and to assess fuel treatment effectiveness. However, these indices often underestimate crown fire potential. Our system of hierarchical fuels characterization and mapping provide opportunities to develop new metrics for 3D fuels useful interpretation and insights to managers, particularly with respect to fuel reduction treatments and prescribed burning programs. Leveraging the STANDFIRE prototype 3D fuel modeling platforms, we will develop metrics quantifying fuel properties and spatial characteristics. In many cases, gaps between fuels may play as important a role in fire spread.

We will develop fuel metrics that statistically characterize not only the distributions of surface and canopy fuels, including horizontal and vertical fuel continuity, but also gap structures in 3D fuelbeds. Our approach will use fractal theory and modeling that treats plant architectures as hierarchically structured, fractal-like, space-filling branching networks (Parsons et al. 2011), and calculate lacunarity, a measure of the distribution of gap sizes across a range of spatial scales (Plotnick et al. 1993). Drawing upon our measurement and modeling of fuel properties, we will also characterize the potential energy within each voxel, and the fire radiative energy density, calculated from empirical relationships with fuel consumption and moisture content (Smith et al. 2013, Klauberg et al. 2018).

Task leads:

- *This will be an integrated task involving all co-Is on the 3D fuels project.*

Landscape Mapping

Comparison of fuel mass, bulk density, and SA:V from previous sections will be related to multi-scale ALS metrics to estimate unit-level fuels and consumption. Using the continuous voxel estimates of fuel characteristics derived from TLS data, we will estimate landscape estimates of fuelbed properties using relationships with a compendium of ALS-derived height metrics, such as maximum height, mean height, height percentiles and canopy densities (**Figure 15**). Examples of the use of ALS metrics in for fuel mapping can be found in Hudak et al (2016) and Garcia et al (2017). In a related study, Rowell (2017) describes improved estimates of landscape scale fuel mass using this method over individual clip plots alone. This method is expected to readily extrapolate to other independent metrics of fuelbed properties (e.g. SA:V, bulk density). For this task, we will be in close collaboration with Andy Hudak on his recently funded SERDP project, "RC20-C3-1346: Object-based aggregation of fuel structures, physics-based fire behavior and self-organizing smoke plumes for improved fuel, fire, and smoke management on military lands."

Task leads:

- *Hudak – lead*
- *Silva – ALS-derived canopy metrics, modeling and mapping*

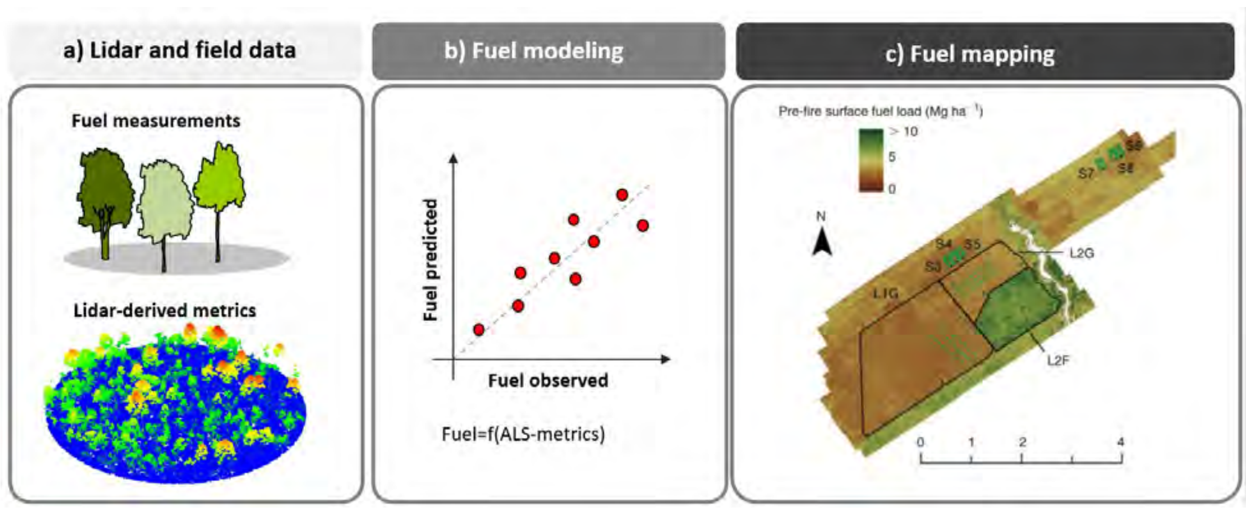

Figure 15. Fuel modeling and mapping from ALS-derived canopy metrics; a) lidar and field data; b) fuel modeling and c) fuel mapping.

Model Sensitivity Analysis

Wildland fuels are complex and highly variable, typically unevenly distributed in space and characterized by clumps and gaps within canopy and surface fuels (**Figure 16**). Heterogeneity in fuel characteristics evolves from the myriad processes in growth of live plants over time (with respect to live fuels) as well as their deposition and decomposition (in the case of dead fuels). The goal of this task is to improve our understanding of how fuel heterogeneity impacts fire behavior, and the implications of scaling to CFD models of fire behavior. Our model sensitivity analysis will address one of the main research questions of the 3D fuels project: *What are the appropriate sampling resolutions of wildland fuels to model fire behavior and consumption, ranging from full physics-based modeling applications to operational models of fire behavior and consumption*?

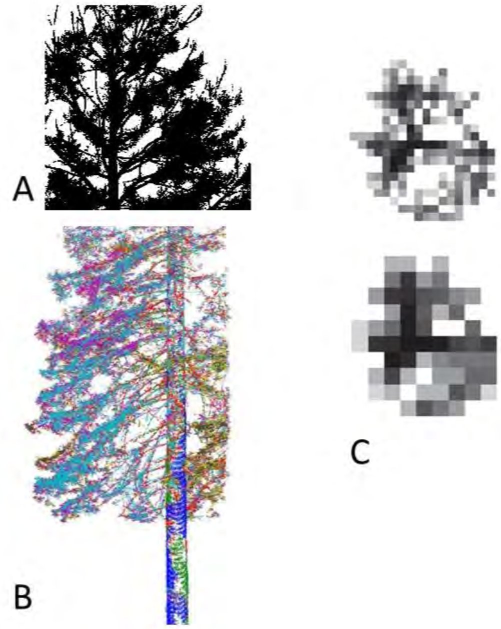

Figure 16: Spatial distribution of canopy fuels within individual tree crowns as shown in profile view (A), TLS-based point clouds (B) and overhead view of voxelized fuels at two resolutions (C).

For this task will use the WFDS physics-based fire model, focusing on assessing modeled fire behavior sensitivity to spatial resolution of, and heterogeneity within, surface fuel components across a range of spatial scales and fire conditions. While there are an increasing number of detailed mapping approaches available including UAS-based high-resolution imagery and Terrestrial Lidar Scans (TLS) point clouds, it is still undetermined how much fine-scale detail is needed to refine model estimates. Fuel mapping efforts should ideally be directed at the aspects of wildland fuels that are most critical to fire modeling, but we currently have little guidance on appropriate scales of measurement.

Fundamentally, sensitivity to fuel heterogeneity and modeled resolution depends on the nature and distribution of that heterogeneity and on the burning conditions under which the assessment is made. Simulation-based sensitivity analyses at forest patch scales suggest that spatial heterogeneity in fuels has a greater impact on fire behavior under more moderate fire weather conditions (i.e., higher fuel moistures and lower wind speeds) than under more severe conditions (i.e. lower fuel moistures and higher wind speeds) (Parsons et al 2017). This suggests

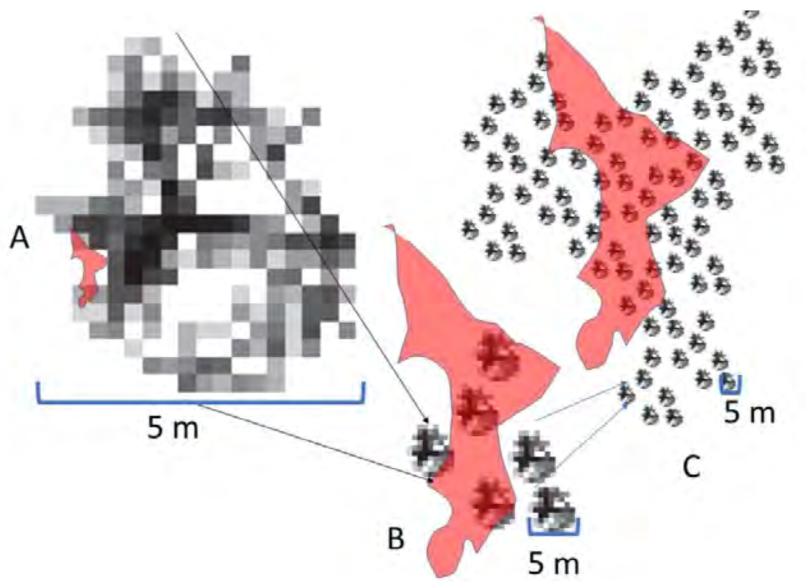

Figure 17: Three hypothetical scales of fire: A) high resolution fuels with a small fire burning into them. Here, we would likely expect higher fire behavior sensitivity to fuel heterogeneity. B) a larger fire in which finer scale heterogeneity of individual shrubs is likely less important than between-shrub heterogeneity, and C) a larger fire in which fuels become more homogenous within the larger fire event.

that sensitivity to fuel heterogeneity is scale dependent. **Figure 17** illustrates three spatial scales of fire from very fine-grained fuel heterogeneity in which within-shrub heterogeneity influences fire behavior; to mid-scale fires in which gaps between shrubs influence fire behavior and a large fire event at which finer scale fuel heterogeneity likely has little effect on fire behavior.

The sensitivity analysis will explore both spatial and compositional heterogeneity within surface fuels, and how those affect outcomes in fire behavior under different fire conditions. Specifically, we are interested in learning how the grid size of surface fuels influences fire behavior predictions (i.e., spread rate and heat release) over a range of fire conditions (i.e., fuel moistures, wind speeds). This task will focus on surface fuels, starting with detailed simulation over small areas examining, for example, single shrubs or grass clumps, and extending out over a range of spatial scales to more operationally tractable resolutions across prescribed burn units. High resolution TLS scans will be statistically summarized, capturing distribution in horizontal and vertical space and different aspects of heterogeneity partitioned. A stochastic 3D fuel distribution model will then be parameterized from this data and used to represent surface fuels within each classified fuel complex (e.g., pine needles, grasses, shrubs and mixed complexes of surface fuels). The sensitivity analysis itself will be carried out using WFDS, simulating each scenario and quantitatively comparing changes in fire behavior associated with each aspect of heterogeneity represented. However, our datasets will be available for other model evaluation, and we anticipate that lessons learned from this analysis will be applicable to FIRETEC/QUICFire and other CFD models.

Task leads:

- *Co-I Parsons and Jesse Johnson (U Montana Computer Science)*
- *Ruddy Mell – WFDS advisor*
- *Eric Rowell – advisor based on recent SERDP-funded limited scope using QUICFIRE/FIRETEC (Rowell 2019)*

Prototype 3D Fuels Applications

Our 3D fuels datasets and modeling steps will be used to generate inputs to CFD models and 3D fuel characterization. These will be used to develop new operational models of fire behavior, smoke and other fire effects. A key advantage of our 3D fuel modeling approach is that voxel fuels are treated as scalable building blocks and the process of partitioning point cloud data into voxel fuel inputs can be widely applied to other fuel types and complexes. In this project, we are focused on some of the most commonly burned fuel types on DoD lands. We intentionally selected geographically distinct vegetation that has similar structures (e.g., southern pine and ponderosa pine forest understories). Through sampling of parallel fuel structures, we will evaluate how the process of 3D fuel characterization at the voxel level can be applied to structurally similar vegetation and fuels and customized to the fuel properties that may vary by species (e.g., S:V, bulk density) and fuel conditions that vary by geographic region and day-of-burn conditions (e.g., fuel moisture).

As a precursor to comprehensive 3D modeling framework, our project will produce a 3D library of voxel fuels, intrinsic fuel properties and quantitative modeling scripts that partition point cloud data into voxels and create 3D input for existing and custom applications. The intrinsic fuel properties library is an integral component of the project, as it will allow us to summarize measured fuel properties (e.g., bulk density, SA:V) and assign them to gridded 3D representations of fuels. Based on our work on quantitative modeling, intrinsic fuel properties and model sensitivity analysis, we plan for the 3D fuels project to lay the groundwork for an eventual application that integrates and parses hierarchically sampled 3D fuels data for next-generation fire behavior and effects modeling.

As a co-I, Parsons is using our methods and datasets to expand two current 3D fuel prototype modeling systems, FUEL3D and STANDFIRE, which model fuels and produce inputs to WFDS and FIRETEC at plant and stand scales, respectively. New metrics of 3D fuel continuity, gap structure, and potential energy release will provide innovative interpretations for fire and fuel managers that will be implemented within STANDFIRE. Our coPI, Eric Rowell, recently completed a SERDP limited scope project that evaluated the sensitivity of QUICFire to fuel inputs. Building on that work, coPI Parsons and colleagues will focus on the sensitivity of WFDS to 3D fuel inputs, including a range of grid resolutions. The synergies between the data collection and mapping and these modeling efforts will help to advance wildland fuels science to improved spatial characterization of surface and canopy fuels.

Task leads:

- *Hudak, Parsons, Prichard, Rowell, Hudak, Silva, Skowronski: coordinate and document scripting tools*
- *Brian Drye – software engineer*
- *Ben Bright – central script repository along with image datasets*

Project Deliverables

- 3D fuel voxel library of commonly burned surface fuels on DoD lands
- Physical fuel property library – web tool repository of published and measured values
- Prototype 3D rendering and QSM scripts – precursor to an integrated system to interpret point cloud datasets into classified maps of 3D fuels and inputs into CFD and next-generation operational models
- Interim methods for quantifying spatial and temporal fuel consumption in 3D
- Improvements to STANDFIRE and informing input resolution requirements to WFDS, FIRETEC and operational models such as WFDS-levelset and QUIC-FIRE
- Manager trainings including Rx410 smoke management and DOD presentations
- Minimum of 8 peer-reviewed papers
- One Master's thesis and two PhD dissertations

The main project deliverable is a prototype method to characterize 3D fuels for use in existing CFD models and next-generation fire, smoke and fire effects modeling to support prescribed burning on DoD installations. We will create a hierarchical fuel sampling and modeling strategy that is both scalable (from local projects to landscapes) and broadly applicable to a wide range of systems (grasslands, shrublands, savannas and closed forests) and management applications (e.g., representations of thinning, prescribed burning and other fuel reduction treatments). As a team, we are referring to this as a necessary step toward producing a next-generation fuel characterization system that houses a library of fuel properties and scripts to convert point cloud imagery to voxelized 3D fuel inputs to existing and future models and modeling frameworks. We will build an online reference library of fuel properties and scripts that can be used to convert point-cloud data to 3D inputs for commonly burned fuels on DoD lands. We will deliver a prototype method rather than a comprehensive system because future development and testing would be needed to create an actual software application that could be used by managers and other fire and fuels specialists, which is more appropriate for an ESTCP project.

As an intermediate step towards a fully integrated 3D fuels modeling framework, we anticipate that results from this project will contribute to the development of 3D fuels modeling that can augment current functionality in FUELS3D and STANDFIRE and increase their applicability for operational use. A promising development in operational fire behavior modeling is the transition from full computational fluid dynamics modeling of fire behavior and combustion to more operational applications such as QUICFIRE, which implements FIRETEC on a coarser grid with rapid computations and WFDS-levelset, which spreads fire based on gridded terrain, fuels and wind inputs. Both implementations can use the full physics-based modes to produce calibrated fire spread and intensity and then model fire progression on coarser fuel meshes and over large landscapes. Our hierarchical approach to 3D fuel characterization, with particular focus on surface fuels, will facilitate the production of both fine-scale fuel meshes for physics-based models and the coarser meshes to be used in current and future operational models for prescribed burning.

Another key deliverable will be a data archive of 3D fuels and consumption that can be used as evaluation datasets to inform operational prescribed burn programs on DoD installations. Sites will be geospatially rectified to allow for coordinated fire behavior, fire effects and plume dynamics studies. Because geospatial data management is an essential component of this project, our geospatial data manager Ben Bright is involved in all aspects of this study and will work to ensure that site data collection, analysis and archiving are standardized across sites. 3D fuels maps will be archived and available for download on our project website and the US Forest Service Research Data Archive.

Data Management Plan

We anticipate the need for coordination and sharing of raw, intermediate, and final data products derived from large datasets for this project. Ben Bright is our project geospatial data manager and is coordinating file storage, sharing, metadata and archiving. Because of the large file size of photogrammetry and TLS scans (2GB or greater per scan with an estimated total of 800 to 1000 files per site), we will need unlimited cloud-based storage and are in conversations with USGS about an eventual 3D fuels online repository.

Raw data (stored with data collector):

1) Field photos and data sheets
- Field photos and site locations (ArcGIS online)
- Raw data from ground-based field sampling (3D fuels drive)

2) Imagery and point cloud data:
- Synoptic ALS, TLS and SfM photogrammetry scans (clean and analysis ready) will be stored in a native ASCII file or converted to las/laz formats
- 5x5m plot-level TLS and SfM photogrammetry point clouds

3) Intrinsic fuel properties:
- Laboratory measurements of sampled fuel particles will be stored with FERA
- A web-based data repository will be created for project data sharing

Intermediate data:
- 3D fuels sampling and traditional sampling data will be entered into the FERA field database. Intermediate files will be stored at the PWFSL with online backups
- Intrinsic fuel properties library (maintained by FERA with online backups
- Intermediate scanned imagery and point cloud products

Final products:
- 3D fuel properties library (online, searchable repository)
- 3D voxels and point clouds
- 3D merged point clouds representing each site
- 3D fuels landscape mapping products including mapped metrics and biomass

Planned Publications

This project will produce a minimum of 8 peer-reviewed research papers and support three Ms students and one PhD student.

List of completed and planned publications

1) Relationships between lidar-derived metrics and biomass mapping (Hudak et al. 2020, Rowell et al. 2020)
2) Interpreting point cloud datasets of understory plant communities: Quantitative models of tall shrubs and understory plants from terrestrial lidar (Bester, Skowronski)
3) Validation of lidar- and phodar-derived bulk density, biomass and other fuel properties (UW Masters Student, Rowell, Loudermilk, Cronan and Prichard)
4) Implications of mapping resolution for CFD modeling (Rowell, Parsons)
5) Hierarchical sampling for 3D fuels mapping applications (Hudak, Prichard, Rowell, Parsons, Skowronski)
6) New metrics from 3D fuels mapping (Rowell, Prichard, Hudak, Parsons)
7) Mapping applications for next-generation fire and smoke modeling
8) Characterization of understory fuels for large-scale fuel and biomass mapping

Safety and Health

Experimental work will be conducted in a variety of Forest Service and university laboratories as well as in the field at various locations (Table 1). Safety and health protocols at laboratories other than PNW Research Station will be covered by local documentation. Safety and health hazards associated with field work - in particular prescribed burns - are described in approved JHAs on file. The FERA field crew has, as a minimum, National Wildfire Coordinating Group Fire Fighter Type 2 qualifications in order to participate in the prescribed burns and other personnel will meet requirements specified by each burn plan. As part of COVID safety and health planning, the FERA field crew is following University of Washington and US Forest Service requirements to maintain and follow approved safety plans for both laboratory and field work.

NEPA Compliance

Fuel sampling will consist of harvesting the above-ground portion of live plants and the dead litter material in contact with the soil surface within areas planned for prescribed burns. The impact will be minimal as the material would be removed by fire otherwise. Prescribed burns will be performed by local managers, and impacts associated with site preparation, the prescribed burns, and smoke will be described in burn plan documents and approved by the appropriate officials. The record of decision by the program manager for this study is based on this analysis.

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Table 4: 3D fuels team.

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Table 5: Project time table.

Task	Activity/Milestone	Lead(s)	2019				2020				2021				2022				2023
			Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1
	Transfer funds to PI institution and complete sub-agreements	Ottmar / Prichard																	
1	Coordination meetings and site selection with staff at candidate sites. Finalize study plan.	Prichard / Cronan																	
2	In-situ 3D fuel sampling	Rowell / Hudak																	
3	Physical fuel properties measurement and library	Cronan / Prichard																	
4	Terrestrial LiDAR system fuel sampling	Hudak / Rowell																	
	Work plan (following preliminary field sampling and including go-no-go decisions)	Ottmar / Prichard																	
5	High/coarse-resolution UAS image acquisition	Skowronski																	
6	Experimental burns	Rowell / Hudak																	
7	Object-based fuel characterization (QSM)	Skowronski / Hudak																	
8	Landscape scale estimates of 3D fuels and consumption	Hudak / Skowronski																	
9	New 3D metrics for fuels managers	Prichard / Parsons																	
10	Sensitivity analysis of spatial resolutions using CFD model simulations	Hudak / Parsons																	
11	3D fuel modeling / STANDFIRE linkages	Parsons																	
	Annual Progress Reports	Ottmar / Prichard																	
	Prepare final report	Prichard / Ottmar																	

List of Abbreviations

2D: two dimensional
3D: three dimensional
CFD: computational fluid dynamics model
CWD: Coarse woody debris, defined as 7.6 cm diameter logs or wood particles
DoD: Department of Defense
DOE: Department of Energy
FCCS: Fuel Characteristics Classification System
FWD: Fine woody debris, defined as < 7.5cm diameter logs or wood particles
Lidar: Light Detection and Ranging laser scanning
NAIP: National Agriculture Information Program
NEPA: National Environmental Policy Act
RGB: red, green, blue band assignments in true-color imagery.
SE: Southeastern
SfM: Structure-from-motion photogrammetry
ALS: Airborne lidar scanning
TLS: Terrestrial lidar scanning (ground based)
UAS/UAV: Unmanned aerial system or unmanned aerial vehicle