FINAL REPORT

Hierarchical 3D fuel and consumption maps to support physics-based fire modeling

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Abbreviations/Acronyms

FASMEE	Fire and Smoke Model Evaluation Experiment
TLS	Terrestrial laser scanning
ALS	Airborne laser scanning

Keywords

Airborne laser scanning, 3-D Fuel Characterization, FASMEE, FIRETEC, Physics-Based Fire Models, WFDS

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Abstract

To meet the data requirements of physics-based fire models and FASMEE objectives, traditional fuel and consumption measures need to be integrated with spatially explicit, three-dimensional data. One of the challenges of traditional fuel measurement techniques is that they must either remove or alter the fuels that are a primary determinant of fire behavior and smoke production. Remote measurement methods can non-destructively provide three-dimensional, point-cloud representations of fuels but still rely on traditional measures to quantify fuel loads, surface-area-to-volume ratios, fuel moistures and other intrinsic properties of fuels. Coupling traditional measurements with remotely sensed datasets can allow for scaling up observations from fine-scale inputs to physics-based models to coarse scale fuels characterization required by smoke models such as WRF-SFIRE-CHEM and DaySmoke. Hierarchical sampling across a range of spatial scales can also provide an important sensitivity analysis of what scale of observations is needed for models of interest.

In the Phase I planning phase of the Fire and Smoke Model Evaluation Experiment, the Fuel and Consumption discipline team specified a multi-scale fuel measurement and modeling framework to characterize pre-burn and post-burn fuels in proposed large-scale prescribed burn units in the southwestern (SW) and southeastern (SE) United States. As proposed by the Fuels Discipline team, traditional measures of fuels will be integrated with remotely-sensed point cloud data to provide estimates of pre- and post-fire fuel mass, volume, or density in physical measurement units and in 3D within the same domain as physics-based fire models. The density and extent of the point cloud and ground-based measurements will be contingent on fuel type and structure, but in general, sites with fine surface fuel beds that vary at sub-meter scales, typical of the SE sites, will be characterized at higher resolution (≤ 1 m), whereas sites with fuel elements that vary at the scale of individual trees, which is more typical in the candidate SW sites, will be characterized at coarser resolution (≥ 1 m). Across all burn units, pre- and post-burn overstory tree crown structure will be spatially characterized using airborne laser scanning (ALS), otherwise known as LiDAR. Where finer-scale surface fuels are the focus, particularly in the SE, Terrestrial Laser Scanner (TLS) and Unmanned Aerial Systems (UAS) derived point clouds will sample fuels at higher resolution within limited extents. Sampling will be conducted in Highly Instrumented Plots (HIPs) or along transects within each operational prescribed burn.

I. Objectives

Our proposal directly responded to the JFSP Task Statement to select a Discipline Lead to guide the fuels and consumption discipline for the FASMEE project. Our central objective was to develop measurements, modeling, and mapping approaches needed to generate 3D maps of heterogeneous fuel beds at hierarchical scales optimized for input into fire and smoke models. The Task Statement also outlined the following roles for each discipline lead:

- Providing expertise to the Scientific Leadership Team for their discipline area;
- Reaching out to the larger scientific community in their area for additional information as needed;
- Proposing an observational study design for observations in their discipline area;
- Working in conjunction with the modelers and the rest of the Scientific Leadership Team to validate their proposed study design;
- Writing up the study design and creating a detailed set of required observational specifications;
- Helping develop a Funding Opportunity Notice to identify and select observational groups;
- Reviewing observational group proposals and integrating selected proposals into the final study plan; and
- Building the final Study Plan.

Our team participated in all collaborative aspects of FASMEE Phase I including 1) providing expertise on fuels, consumption and proven multi-scaled remotely sensed and field sampling methods; 2) consulting other scientists and instrument specialists on feasibility of various measurement techniques, including investment into analyses of existing datasets for developing point-cloud based fuel modeling methods; 3) developing a observational study design for fuels and consumption; 4) closely collaborating with modelers, other discipline team leads and the FASMEE Phase I Leadership team through bimonthly meetings, field trips and planning/writing retreats; 5) proposing a detailed set of observational requirements, and helping to draft early drafts of the FASMEE study plan.

II. Background

The Phase I FASMEE fuels and consumption discipline team was formed to provide observational requirements for the Phase II measurement campaign. The Fuels and Consumption team worked closely with the other disciplines (Fire Behavior and Energy, Plume Dynamics and Meteorology, Smoke and Emissions, and Fire and Smoke Modeling teams) to develop measurements requirements and the FASMEE study plan. Because fuels and consumption are key inputs for all fire and smoke models, we focused on fuels characterization needs for the most data-intensive models to ensure that minimum observational requirements for fuels and consumption would satisfy the entire range of fire and smoke models -- from relatively simple operational models such as BehavePlus (Andrews et al. 2005), FlamMap, Consume (Prichard et al. 2007) and FOFEM (Reinhardt 1997), to complex, physics-based models such as WRF-SFIRE-CHEM (Mandel et al 2011, 2014), WFDS (Mell 2007, 2009) and FIRETEC (Linn et al. 2002, 2005).

Based on modeling needs from each fire and smoke modeling team, the FASMEE fuels and consumption team addressed:

1. Basic fuel properties including fuel type, biomass by fuel category, structure (height/depth and cover, and moisture content).
2. Three-dimensional characterization of pre-burn and post-burn fuels
3. Pre-and post- characterization of fuels to quantify consumption and combustion phase (flaming, smoldering and residual smoldering) and to be used as source characterization for smoke and emissions measurements.

For spatial mapping and characterization of pre- and post-burn fuels, a nested sampling design can be tailored to the actual scale of fuel structure variation in each study site location. Airborne LiDAR provides synoptic coverage for mapping wall-to-wall overstory vegetation, and, with less sensitivity, lower-level canopy and surface vegetation layers. At smaller scales, multi- or hyperspectral imagery from UAS and/or towers/tethered balloons provide mid-scale fuels mapping and also assists with fuel type characterization and status (live/dead). Surface fuel components and fuel properties can be intensively sampled within HIPs or at systematic intervals along transects in sites with dense, multi-layered vegetation. Surface fuel measurements from accurately geo-located HIPs or transects can also be scaled up to make unit-level inferences.

III. Materials and Methods

3.1 Study area descriptions and locations

Four candidate study areas have been selected for the FAMSEE experimental burns including two sites in the SE and two sites in the SW. FASMEE plans to conduct at least one large, operational prescribed burn in each region.

Candidate locations in the SE include Fort Stewart (US Army Installation, SW of Savanna, GA) and the Savanna River Site (US Department of Energy, SE of Augusta, SC) (Figure 1). Sites will be targeted to have heavier than normal surface fuel accumulations with at least 3 years since fire (3-5 year rough) but are still representative of sites commonly burned in the region (southern pine forests with grass and shrub understories). The burn(s) will be conducted on large units (> 500 acres) during conditions that favor a high-intensity surface fire and large plume development.

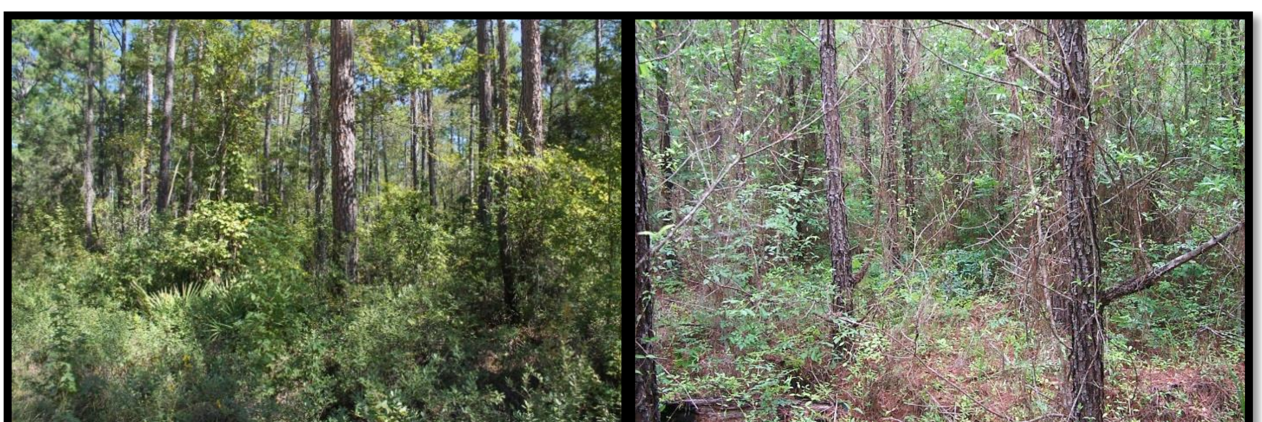

Figure 1. Left panel: 4-year rough in a longleaf pine/loblolly pine forest, Fort Stewart. Right panel: >4 year rough in a loblolly pine forest, Savannah River Site.

In the SW, candidate sites include the Richfield Ranger District of the Fishlake National Forest in Utah and the North Rim of the Grand Canyon/Kaibab National Forest which are managed through a collaboration between Grand Canyon National Park and the US Forest Service. The Fishlake site is a fire-excluded, mixed conifer and aspen forest, located at higher elevations (>7000 ft) on Monroe Mountain in the Richfield Ranger District. Surface fuels are comprised of heavy downed wood and forest floor fuel accumulations (60-100 Mg/ha) (Figure 2). The Kaibab site has two candidate forest types including high elevation mixed conifer with multi-layered canopy fuels and heavy surface fuels (>60 Mg/ha) (Figure 2) and lower elevation ponderosa pine forest with light surface fuels (~10 Mg/ha) (Figure 3).

Figure 2. Left panel: Mixed conifer-aspen forest, Monroe Mountain Richfield District, Fishlake NF. Right panel: Mixed conifer-aspen forest, Tipover Unit, North Rim, Grand Canyon NP.

Figure 3. Ponderosa pine forest, Jacob Lake, North Kaibab NF.

3.2 Background: Three Dimensional Fuels Characterization

LiDAR is currently the most advanced remote sensing technology for 3D characterization of vegetation and fuels. Point clouds capture the 3D spatial distribution of fuel elements like no other method can, but do not directly measure fuel load or bulk density. Although measures of vegetation height, cover, and relative density can be derived directly from point cloud data without field data, traditional field measures of fuels in mass units are also needed to estimate fuel load and bulk density from point cloud data. Establishing this linkage between point cloud observations and field measurements is an essential step in calculations of fuel consumption (e.g., Mg/ha) that can be related to fire radiative energy and emissions.

Successful evaluation of fire and smoke models requires accurate representation of fuels and environmental conditions at the time of the fire. To best leverage information across a series of burn experiments spanning different sites and diverse fuel types, as planned in the FASMEE project, it is highly desirable that the process used to represent fuels and environmental conditions be repeatable, systematic and quantitative. In recent years, physics-based fire behavior models such as HIGRAD/FIRETEC (Linn et al 2005) and WFDS (Mell et al 2009) have had an increasingly important role in improving our understanding of wildland fire, particularly with respect to how different aspects of wildland fuels affect fire behavior. The capability of these models to address fuel heterogeneity is critical to the potential success of the FASMEE project and other such efforts. However, despite the power of these models, they have not yet been widely used, largely due to the complexity required in developing inputs. The STANDFIRE prototype fuel and fire modeling platform (Parsons et al. 2017), developed with support from the JFSP (JFSP Project #12-1-03-30), is intended to ease this burden, providing a process by which fuels data can be used to rapidly develop 3D fuels inputs to physics-based fire models. Building upon previous work, Fuel3D (Parsons et al. 2011), STANDFIRE's open source software, developed in python and Java, links fuels data in the Fire and Fuels Extension of the Forest Vegetation Simulator (FFE-FVS; Reinhardt and Crookston 2003) through a state-of-the-art fuel modeling system (Pimont et al 2016), producing fuels inputs for two independent physics-based fire models, WFDS and FIRETEC. In support of the FASMEE project, STANDFIRE was modified to provide a framework for linking traditional fuel measures to point cloud data at tree to stand scales. In the project reported on here, we use Airborne Laser Scanning (ALS) data with Terrestrial Laser Scanning (TLS) data and parametric plant models to link LiDAR metrics with fuel load data at multiple scales. We also derive the spatial variability of surface fuels across scales and parameterize STANDFIRE with ALS-derived models of individual trees. The work is described in two phases: surface fuel characterization, conducted in Southeastern US fuel beds, and canopy fuel parameterization, conducted in the Northern Rockies. Both aspects of this project contribute significantly to development of required data collection and analysis protocols for the FASMEE project. These efforts are parts of a larger framework for integrating measurements of fuels across scales to support fire modeling validation efforts (Figure 4).

3.3 Case Study

Existing datasets of fuel conditions similar to the settings described above were analyzed in a case study to improve our understanding of the novel point-cloud based fuel characterization methods that underpin the FASMEE fuels discipline. The 3D fuels portion of the case study progressed in five stages 1) fine-scale determination of surface fuels as determined from high resolution TLS for both grass/shrub and forested fuels in the SE; 2) refinement of surface fuel type and fuel load allocation based on highly realistic fuelbed simulations; 3) aggregation of TLS and ALS estimations of surface fuelbeds; 4) estimations of ALS-based canopy fuel loading and distributions; 5) integration of ALS canopy fuels in STANDFIRE and parameterization for computational fluid dynamics fire behavior models. The remote sensing data sets used for these analyses were collected at Eglin Air Force Base (AFB), Florida, USA as part of the RxCADRE experiments and at Lubrecht Experimental Forest, Montana, USA as part of a LiDAR inventory of forest attributes. Field measurements of fuels were collected as part of RxCADRE in 2012, Strategic Environmental Research and Development Program (SERDP) in 2014, both at Eglin AFB. Forest inventory data were collected at Lubrecht Experimental Forest in western Montana in 2006. These existing datasets were analyzed as proxies given their similarity to those anticipated for collection at the proposed FASMEE sites.

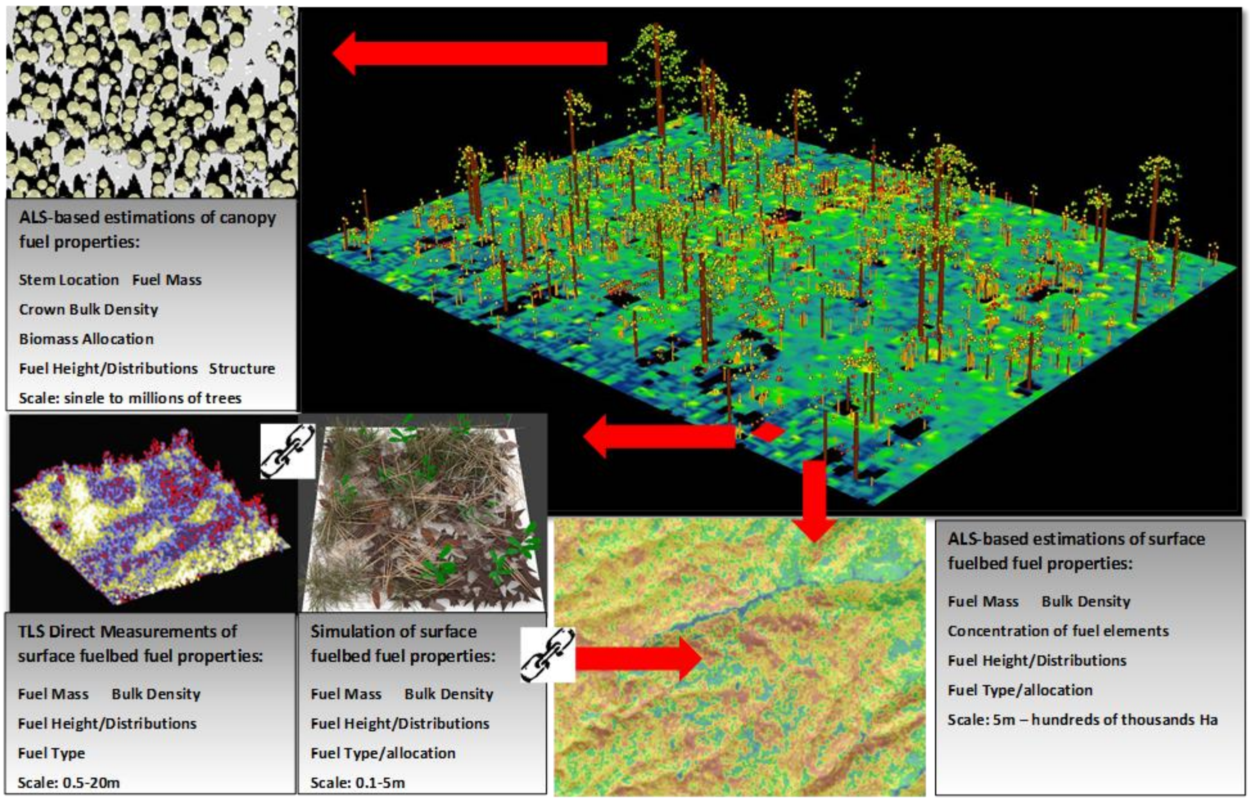

Figure 4. Schematic of the the larger framework that airborne laser scanning, terrestrial laser scanning, and fuel simulations play in characterizing landscape fuels.

3.3.1 Case study site descriptions

The surface fuels portion of the study focused on characterizing fuelbeds in the SE for both grass/shrub matrices and forested southern rough. Dominant species for the grass\shrub sites included multiple species of graminoids and shrubs as woody goldenrod (*Chrysoma pauciflosculosa*), lowbrush huckleberry (*Gaylussacia dumosa*), gopher apple (*Licania michauxii*), saw palmetto (*Serenoa repens*), persimmon (*Diospyros virginiana*), and hawthorne (*Crataegus* spp.) (Ottmar *et al*. 2016). Shrub species in the in the longleaf pine (*Pinus pulastris)* dominated overstory include turkey oak (*Quercus laevis*), sand post oak (*Q. margaretta* Ashe), blue jack oak (*Q. incana* Bartram), sand live oak (*Q. germinate* Small), and laurel oak (*Q. laurifolia*) (Hiers *et al.* 2007).

The canopy fuels portion of the study focused on characterizing fuels canopy fuels at scale of individual trees in ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Psuedotsuga menzesii*) forests within the Lubrecht Experimental Forest's Fire-Fire Surrogate Study. The 11,000 ha

Lubrecht Experimental Forest is located approximately 54 km northeast of Missoula, Montana, USA (N 46º 53' W 113º 27'). The siteis characterized dominated by open and moderately dense stands, a function of the intensive management strategies that occur on the forest. The stands utilized in this project are the Thin, Burn, Thin/Burn and Control treatments of the Fire-Fire Surrogate experiments.

3.3.2 Field Measurements

At Eglin AFB in Florida, validation data were collected as part of the RxCADRE experiments in the fall of 2012. Two modes of data were collected to represent small research prescribed fires (2 ha) and large operational prescribed fires (>125 ha). The small research burns had 25 1x1 m sample plots dispersed at 10-m intervals around the edge of the each unit (n=125). The large operational burns had 20 x 20 m highly instrumented plots (HIPs) were distributed at 2.5-m intervals around the edge of the HIPs with nine 0.5 x 0.5 m sample plots in the grass\shrub units (n = 54) and twelve 0.5 x 0.5 m sample plots in the forested units (n = 36). Dry weight biomass samples were clipped from the plots and collected by four general categories: shrub, herbaceous (grass and forbs), down-and-dead fine wood (≤ 7.6cm in diameter), and litter (Ottmar *et al.* 2016). Samples were oven-dried at 70°C in preparation for weighing and fuel load determination.

In Montana, validation data for individual tree stem detection were conducted at sixty-one 0.04 ha (0.10 acre) square plots using procedures outlined in the Fire Effects Monitoring and Inventory Protocol (FIREMON) tree sampling methods (http://frames.nbii.gov/projects/firemon/TDv3_Methods.pdf; Table 1). Plots were located using a stratified random sampling design. A random point generator was used to place points in the project area, and these points were then stratified using a structural classification of height variance and percent canopy cover derived from the ALS-based Canopy Height Model (CHM; described below). At each plot, all trees >7 cm Diameter at Breast Height (DBH) were measured for height, DBH, height to crown base (HTCB), and crown diameter. Trees less than seven cm DBH were counted by species (coniferous), ocular estimates of minimum, mean, and maximum height were made for each species class. Each tree was mapped using a laser range finder (Laser Tech Forest Pro) attached to a digital compass (Mapstar Compass Module II) on a range staff. Trees were mapped from fixed GPS (Timble Geoexplorer 2500) points around the plots and integrated into a GIS. A total of 1555 individual trees were mapped using this method. No thinning or fire occurred at the study plots between the laser altimetry acquisition and subsequent field campaign. All GPS points were differentially corrected when accuracy exceeded the real-time code carrier. The maximum position dilution of precision (PDOP) averaged 5.77 (standard deviation = 1.70) with the highest PDOP values occurring in dense overstory plots. Horizontal accuracy was approximately 50 cm, with the most accurate GPS points attaining an accuracy of 20 cm and the least accurate GPS points nearing 2 m accuracy in high density canopy conditions.

3.3.3 Terrestrial Laser Scanning – Southeastern US

For this case study analysis, TLS data were collected at Eglin AFB. The instrument used was the Optech Intelligent Laser Ranging and Imaging System (ILRIS^{TM}) 36D-HD TLS. This system uses a class I laser (1535 nm) wavelength), including a range of 3 to 1500 m with a 0.17-mrad divergence (17.6 mm spot spacing at 100m). This laser was employed to test the efficacy of characterizing unit fuels across multiple scales and toproduce models that predict fuels as a function of voxel determined occupied volume tied to *in situ* fuels measurements.

Laser scans were completed pre-and post-burn using an Optech ILRIS^{TM} 3_6D-HD instrument scanning at 10 kHz. As noted above, two modes of data were captured for the RxCadre project, including 1) six S-blocks representing relatively homogeneous and continuous grass fuels interspersed with shrubs over 100 x 200-m extents and 2) the 0.04 ha HIPs located within large operational prescribed fires and comprised of a range of fuel characteristics including homogenous grass, mixed grass shrub fuel, and longleaf pine southern rough fuel matrices. TLS sampling protocols for the HIPs plots were designed to capture overhead representations of fuel beds at ~8 mm spot spacing. The laser was mounted in an articulating boom lift and raised to a height of 20m above ground with a downward pointing tilt angle of 45°. The scanner was operated from the ground using a tablet computer with a WIFI connection. At full extension of the boom lift, the scan head was positioned nine meters horizontal from plot edge. A single scan captured the entire plot. For instances in forested HIPs, data were collected from 3-7 perspectives at variable heights to minimize occlusion of the fuel bed by tree boles and canopies.

In the S-blocks, the TLS instrument was also positioned in the mobile boom lift at height of 20 m above the fuel bed. Laser scans were collected at six positions around each burn block 20 m horizontal from the edge of the block for each scan position. Post-fire scans were collected from the east and west positions only for a total of four per block. In each scan, the laser was pointed downward at an angle of 23°. Scanner settings were optimized to achieve consistent point density across the block with the caveat that point density necessarily declines as range increases. The ILRIS laser allows point density to be set as a function of focal distance; all S-block scans were set to collect 2 cm spot spacing at 90 m. Time of flight scanners collect richer datasets near the point of origin of the scan with less dense point spacing as range increases. As the laser pulse moves away from the ILRIS instrument, the point spacing increases linearly with range at a rate of 16.8 mm per 100 m of range. Additionally, the illuminated footprint of the scanner increases linearly with range, becoming less sensitive to canopy gaps as spot size grows larger (Seielstad *et al.*, 2011). Spot size in the foreground of each S-block was 16 mm, expanding to 29 mm at 100 m range.

TLS data were processed from the raw data format using the ILRIS parser. These data were adjusted for side-lap incongruities between 40°x40° windows using Polyworks software (Innovmetric, Quebec, Canada). Once acceptable accuracy of scan swaths was achieved, scans from single scan points were merged into a single dataset.

3.3.4 Airborne Laser Scanning

At Eglin AFB, discrete-return LiDAR data were collected on 3 November 2012 by Kucera International employing a Leica ALS60 instrument. A 1-m DTM was interpolated from the vendor-classified ground returns using the GridSurfaceCreate function of FUSION software (McGaughey 2014). The 'minimum' value was used rather than the default 'mean', such that the DTM took the value of the minimum elevation value in each grid cell. This lowers the DTM slightly so that the majority of near-ground returns will be above the DTM and hence have positive height values. The ClipData function of FUSION was used to clip, 200–300 points within a 3-m radius of clip plot center coordinates. The DTM was subtracted from the point cloud to normalize absolute point heights to relative heights above ground. Using the CloudMetrics function of FUSION, canopy height and density metrics were calculated from LiDAR returns 0–2 m above ground and within a 3-m radius of each pre-fire clip plot.

Candidate metrics for predictive modelling included the mean, mode, standard deviation (s.d.), coefficient of variation (CV), skewness and kurtosis statistics calculated across the 0–2 m height range; as well as mean, mode, standard deviation and CV and proportion of all returns calculated within vertical strata of 0–0.05, 0.05–0.15, 0.15–0.50 and 0.50–1.0 m above ground. The stratum depths were intended to be unequal because the LiDAR returns are denser nearer the ground, where there is more vegetation and fuel to intercept the laser pulses, than higher above the ground.

In Montana, Laser altimetry data were collected at nominal 1.5-m post spacing in June 2005 for the LEF using a Leica Geosystems ALS50 flown at 1900 m above mean terrain (AMT) with a 35° scan angle (Horizons, Inc., Rapid City, South Dakota, USA). The acquisition was planned so that there was fifty percent side lap between all flight lines, effectively doubling native data density. Following acquisition, data were processed to correct for roll, pitch, and yaw using proprietary software developed by the vendor (Horizons, Inc.). Data were delivered in the American Society for Photogrammetry and Remote Sensing (ASPRS) developed LAS standard format for laser altimetry data (www.lasformat.org).

Aboveground points were separated from the ground points using Terrascan (Terrasolid, Helsinki, Finland). Several iterations were used to refine the optimal settings that preserved important features (e.g. roads) and classified most aboveground points as canopy. As a result of the parameters used, it is worth noting that near-ground points that may have been low-lying vegetation were included in the ground classification in several areas; resulting in so called "les moutons" in the digital elevation model (DEM). These points were not added back to the CHM because they were sparsely distributed, less than one meter in height above 'ground', and there was no basis for determining their origin (e.g. rock, earth, and vegetation).

3.3.5 Surface Fuel Modeling – Southeastern US

Voxels are three dimensional pixels that allow for volumetric representation of discontinuous surfaces using a regularly spaced three-dimensional grid (Stoker 2009). Each voxel point is enumerated with a single value from a data point describing discrete information for the location on the voxel array. A benefit of voxel analysis is the ability to depict areas of data presence or absence. Thus, in the domain of characterizing fuel beds, voxelization allows for the ability to examine fuel connectivity in three-dimensions, which is paramount to understanding where fuel elements exist and how they are distributed in space (Figure 5).

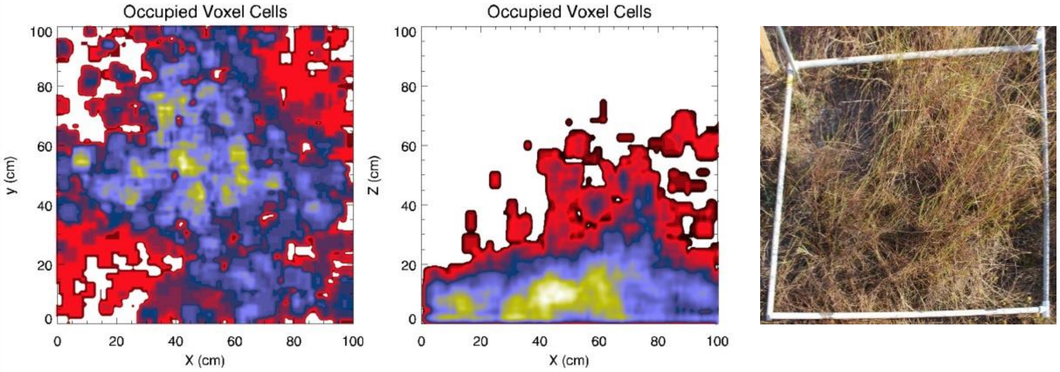

Figure 5. TLS-based 1cm voxel depictions of a grass dominated plot in the S-Blocks collected as part of the RxCADRE experiments. Red colors represent low density and yellow to white represent highest voxel densities.

For the purposes of this study, a 10 cm^3 voxel resolution was selected based on three criteria: 1) that within the shrub grassland matrix 10cm^3 voxel cells allow for characterization of both clusters of grass clumps (grass blades are typically ≤ 1cm in width) and larger shrub components (e.g. leaves and branches > 1cm in width); 2) This grain size preserves gaps between clusters of fuel elements, any larger (e.g. > decimeter) begins to fill gaps and generalize the fuel bed in ways that limit further analysis. Lastly; 3) Each individual scan is optimized to produce a 2 cm point spacing at 90m range, the combination of multiple scan angles produces a range of point densities from 2 points per cm^2 to 8 points per cm^2. Models developed for estimating fuels via TLS are reported at scales ranging from 0.25m2 and 1m2 due to field sampling scales. We use a Leave-One-Out-Cross-Validation (LOOCV) method to model the relationship between observed dry weight biomass and TLS occupied volume. To aggregate to coarser ALS scales, we aggregate the TLS derived fuel mass into 25 m^2 cells representing the total mass for each pixel.

3.3.6 Parametric Surface Fuelbed Simulations – Southeastern US

We constructed spatially-explicit, highly-resolved, and realistic fuel beds using tools developed for 3D animation and modeling for the purpose of studying interactions between LiDAR point clouds and specific fuel attributes. Each fuel element/type (e.g. shrub, grass, needle, etc.) was discretized in the fuelbed, allowing for direct accounting of metrics such as height, volume, cover, surface area, density, and mass. We then examined the fuelbeds through comparison with *in situ* nadir imagery and field measurements, and explored the utility of these models as tools to better understand spatial variability in fuel properties and to improve remote sensing of fuel beds and fine-grained fire modeling. Finally, we compared simulated fuelbed height distributions with

TLS-derived height distributions to assess correspondence of the two methods as a preamble to future incorporation of LiDAR ray-tracing for simulating TLS.

Our effort centered on a main objective of developing realistic and quantifiable simulated surface fuelbeds in longleaf pine ecosystems. We first generated fuel simulations from parametric plant models using high resolution nadir photo imagery (Figure 6) and detailed height measurements and parameterized them with biomass estimates for discrete fuel elements. We then transposed the models to an independent validation site and compared biomass estimates to actual dry weights. Finally, we derived and contrasted height distributions from the simulations and TLS data.

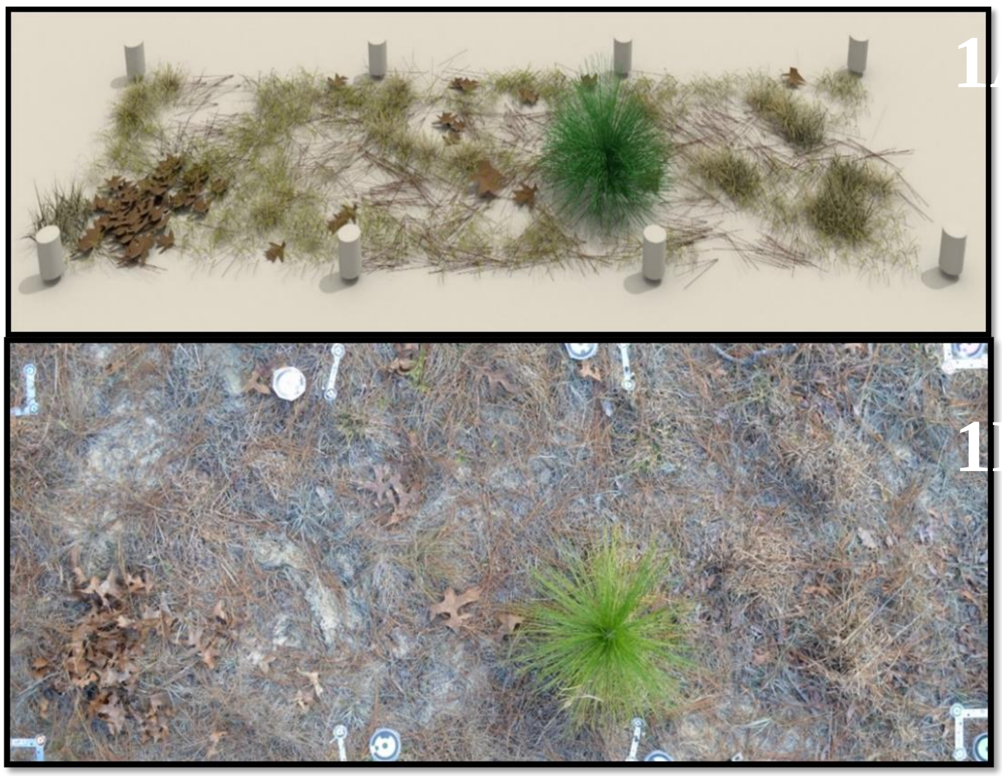

Figure 6. Example of highly realistic fuelbed simulations that offer the ability to segment out fuel mass predictions by fuel type and bridge between field and TLS data. 1A) depicts the fuelbed simulation and 1B) is a nadir photo used to place plant, litter, and cone models.

3.3.7 Stem Detection Algorithm – Northern Rockies

The fundamental framework of selecting a tree location is the utilization of a local maximum (LM) filter (Popescu and Wynne 2002) and the integration of a structural parameter (Rowell *et al.* 2006). The process utilizes neighborhood metrics of height variance and canopy point density within the neighborhood to adjust the expected crown widths of candidate trees. A search within that expected crown width identifies whether a higher point than the candidate point exists. If it does not, the candidate point represents a tree. Rowell *et al*. (2006) outline the combination of height variance and canopy cover for adjusting expected crown widths, where variance of height provides a metric related to the complexity of vertical structure, and percent canopy cover offers insight into the horizontal continuity of tree crowns which may influence expectations for crown size. The model uses these basic constructs as a way to determine the constriction and expansion of the expected crown diameter for predicting local maximums.

The LM filter has been outlined extensively (Wulder *et al*. 2003; Popescu and Wynne 2004; and Rowell *et al*. 2006). The algorithm described in this study subsets the point data using Euclidean distance from a point of interest, then segments to a local area based on the estimated crown diameter of the point being evaluated. As mentioned previously, the logic of LM filtering is to search for points in the expected tree crown that may be higher than the point being observed. As all points carry a normalized height above ground in their attributes, a filter compares all other points in the local area and performs the height comparison. When a point of interest is higher all than surrounding canopy points, it is tagged as a tree. The search area is dynamic as it is based on the estimated crown diameter as a function of height and structural parameters.

3.3.8 STANDFIRE Integration – Northern Rockies

STANDFIRE is a prototype fuel and fire modelling system developed primarily for detailed analysis at stand scales of fuel treatment effectiveness (ADD JFSP PROJECT NUMBER). STANDFIRE is also well suited for evaluating other fuel changes, such as beetle kill, shrub encroachment or exotic annual grasses. The initial design of STANDFIRE was intended to enable users to get their local fuels data, typically in an FVS tree list, into the physics-based fire models. Because the overwhelming majority of fuels data used by most managers is not spatially explicit (i.e., stem-mapped stands), it was necessary to develop a process to generate 3D data. Thus, we built a data import process that leveraged the Stand Visualization System (SVS) files, used in FVS to display forest growth and management actions over time for a one acre area. This import process bypassed the lack of spatially explicit data for most users, and provided an intuitive link between the visualizations that users are accustomed to and fire simulations with the physics-based models. Importantly, it also facilitated simulations for larger areas such that the fire could develop outside of, and then burn into the SVS stand, used as a focal point for analysis (Figure 7).

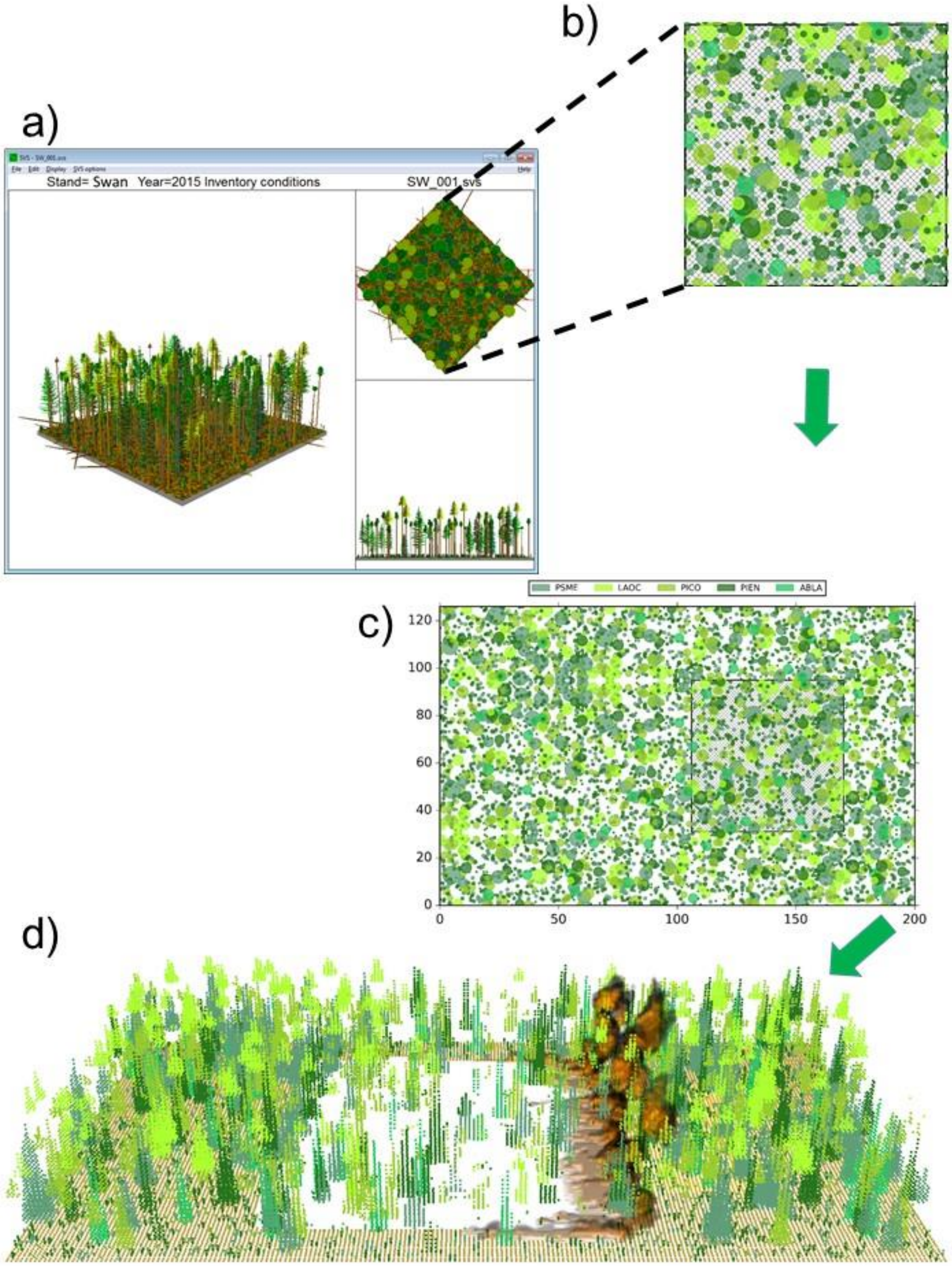

Figure 7. Illustration of STANDFIRE, a prototype system for 3-D fuel and fire modeling at stand scales. STANDFIRE runs FVS and SVS (a), and appends biomass data for individual trees from FFE-FVS to the tree coordinates in the SVS one-acre visualization (b), statistically extending that forest to a larger area specified by the user (c). These data are translated from 2-D to 3-D, populating voxels (3-D cells) with quantitative fuel properties for 3-D fire simulations (d).

IV. Results and Discussion

4. Case Study Results

4.1 TLS Characterization of Surface Fuel Loading – Southeastern US

Estimates of occupied volume produced from the voxel analysis demonstrate strong relationships with total dry weighed biomass collected around the perimeters of the research and operational burn units. For the operational units, characterization of both forested and grass\shrub models explained 84% (Adj. $R^2 = 0.84$) and 71% (Adj. $R^2 = 0.71$) of the variability respectively (Figure 8).

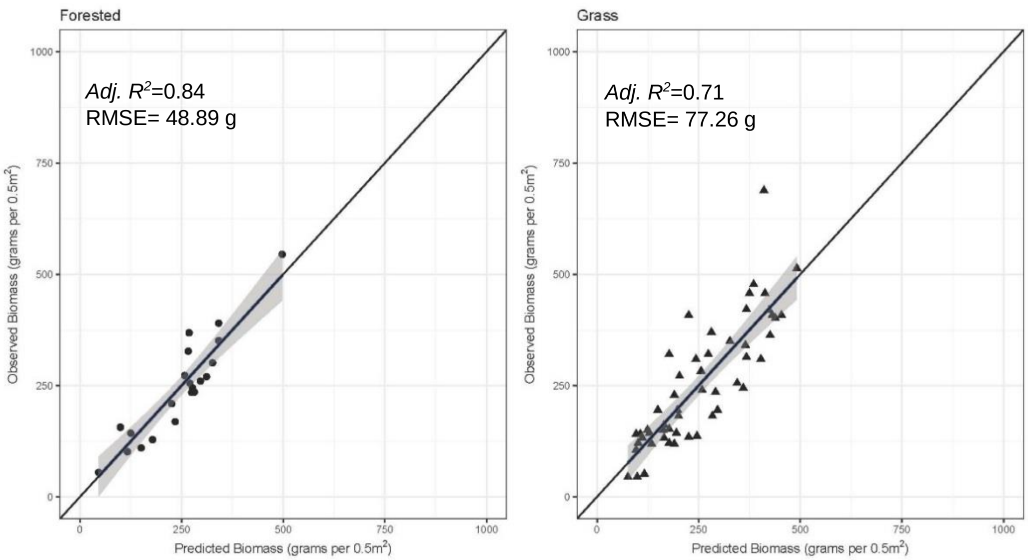

Figure 8. LOOCV linear regressions for pre-fire fuels for the HIPs plots based on the relationship between TLS occupied volume and observed dry weight biomass.

Estimates of total fuel load in forested fuelbeds indicate a 19.5% error (RMSE = 48.89 g) and grass\shrub modeled estimates indicated a 29.7% error (RMSE = 77.26 g). In regards to the research burns (S-Blocks) overall model performance for all units combined explained 63% of the variability (Adj. R^2 = 0.63; RMSE = 111.65 g). These units were characterized as grass\shrub matrices with individual block performance ranging from adjusted R^2 of 0.63 to 0.87 (Figure 9). These results mark a successful first attempt at using TLS based volumetric analysis to predict total fuel loading across burn units. Others have been successful at predicting biomass at shrub scales using voxel analysis and estimated surface area in sage brush steppe and arctic species (Olsoy *et al.* 2014; Greaves *et al*. 2015). Our findings demonstrate the effectiveness of direct TLS measurements of occupied volume to predict surface fuels even when fuel density varies within the fuelbed as a factor of fuel type, with important implications for scaling fuel estimates in the FASMEE experiments.

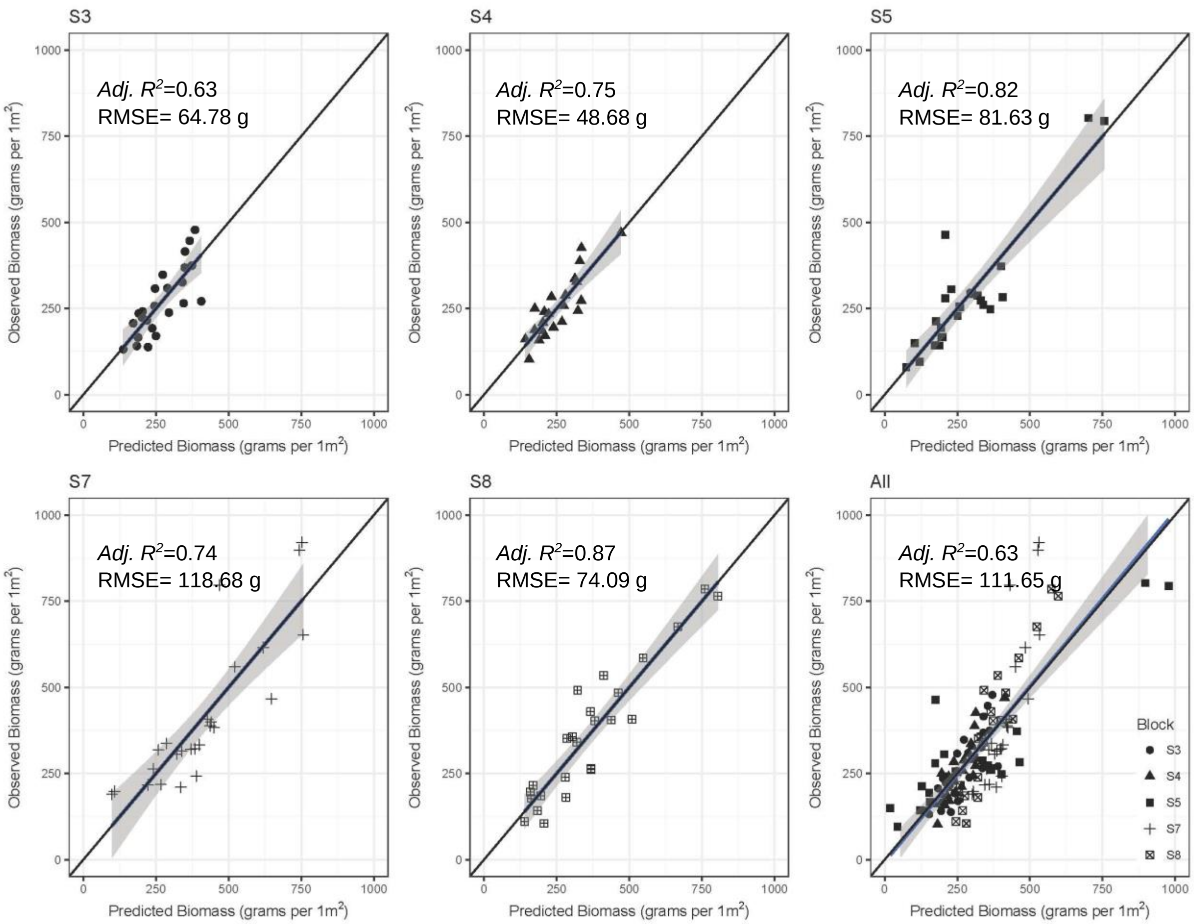

Figure 9. LOOCV linear regressions for pre-fire fuels for the S-Blocks based on the relationship between TLS occupied volume and observed dry weight biomass.

4.2 Linking TLS Fuels and ALS Surface Metrics – Southeastern US

Pre-fire fuel loads for the combined grass\shrub and forested sites demonstrate that surface metrics from ALS are strong predictors of TLS-based total fuel load across the landscape (Adj. $R^2 = 0.71$; RMSE = 0.008 Mg) (Figure 10). TLS-based fuel load predictions (25 m^2) were non-normal as tested by the Shapiro-Wilk test ($W = 0.9264$, $P < 0.0001$) and did not achieve normality using alternative transformations. Residuals from the model were normally distributed ($W = 0.9939$, $P = 0.91$). The range of fuel predictions encompassed similar ranges of observed TLS-based fuels. Bootstrap tests of equivalence rejected the null hypothesis of dissimilarity ($P = 0.0025$), which suggests that predictions and observations were similar with no bias or disproportionality (Robinson *et al.* 2005). Of the nine potentially significant ALS surface metrics described in Hudak *et al.* (2016), only five were significant as predictors of TLS-based fuels. The approach of using aggregated TLS-based total fuel load also produced a landscape estimate for total fuel load per 25 m^2 cell which is a distinguishable difference from the previous study that assumes a fuel average per hectare. We demonstrate improvements on utilizing ALS data surface metrics, as the model explains 27% more of the variability of the observed fuel loads then reported in Hudak *et al.* (2016).

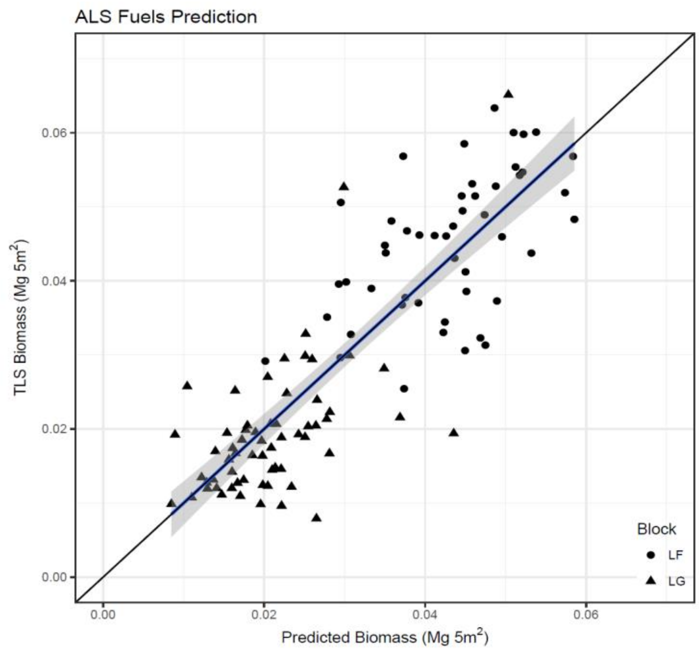

Figure 10. Multiple linear regression model predicting pre-fire fuels using five ALS metrics from TLS biomass.

4.3 Tree Stem Detection – Northern Rockies

The stem detection algorithm predicts overstory trees ($R^2 = 0.74$) with an RMSE of 10.35 stems at densities up to 1500 stems per hectare). Stem density is generally under-estimated on plots with high stem counts, although only two plots had stem counts greater than sixty. Considering only plots with less than 1500 stems/ha (sixty stems per 0.10 acre plot), RMSE declines to 6.86 and R^2 increases to 0.78. Mean heights of ALS-estimated overstory trees are related to field height ($R^2 = 0.91$; RMSE = 1.80 m). For intermediate stems, we observe a linear relationship between laser-predicted and field-observed stems ($R^2 = 0.40$; RMSE = 8.28 stems). The percent error (PE) for intermediate stems (76.84%) is more telling of the variability associated with stem prediction for this canopy class than the RMSE. The results reflect the fact that intermediate stems at LEF are usually nested in the canopies of dominant trees or are clustered tightly within canopy gaps. The number of intermediate stems is more consistently under-estimated than over-estimated and the magnitude of difference between observed and predicted is generally larger on plots where intermediate stems are under-estimated. Mean heights of intermediate stems indicate a strong relationship with observed mean heights ($R^2 = 0.83$; RMSE = 4.55 m). Percent error is relatively small (13.12%) reflecting a tight range of heights for this canopy class. There is a positive bias in predicting mean height of intermediate trees (mean bias = 0.23 m). Trees in the regeneration class were predicted with large error (R^2 = 0.39; RMSE = 21.45 stems; PE = 91.32%). There does not appear to be a systematic under- or over-prediction trend. There is no obvious relationship between laser-based mean tree height and observed mean tree height for the regeneration crown class (R^2 = 0.02; RMSE = 1.87 m).

4.4 STANDFIRE – Northern Rockies

As a prototype, STANDFIRE will continue to develop, adding new capabilities to facilitate new approaches or to incorporate new science as it becomes available. For FASMEE, we modified STANDFIRE to read in stem maps and associated topography built from ALS data, enabling 3D fuel modeling for real world sites. This is an important step for model evaluation projects such as FASMEE. The new process leverages the stem detection algorithm to produce ALS-based stems and associated tree attributes outside of STANDFIRE, including the stem location, tree height, height to crown base, and crown diameter. Tree diameters are modeled from tree crown dimensions. Because ALS data are generally not detailed enough in intensity values or data density to determine individual species for each tree, species are assigned within the process based on user-specified proportion of species occurrence.

Within STANDFIRE, FVS uses allometric relationships based on tree DBH to predict bole and canopy biomass quantities. The LiDAR-driven data process in STANDFIRE relies on the SVS file to append biomass quantities to individual trees. As SVS is limited to 1 acre parcels, we developed the process to automatically tile the data into ~ 1 acre square sections. The process is coded in Python and takes advantage of the ArcGIS API, facilitating use of shapefiles as input data for stem mapped trees as well as several operations in which specific trees are associated with specific 1 acre areas. Figure 11 shows an overhead perspective of a representative six acre area, and Figure 12 displays the same data overlayed with color infrared imagery.

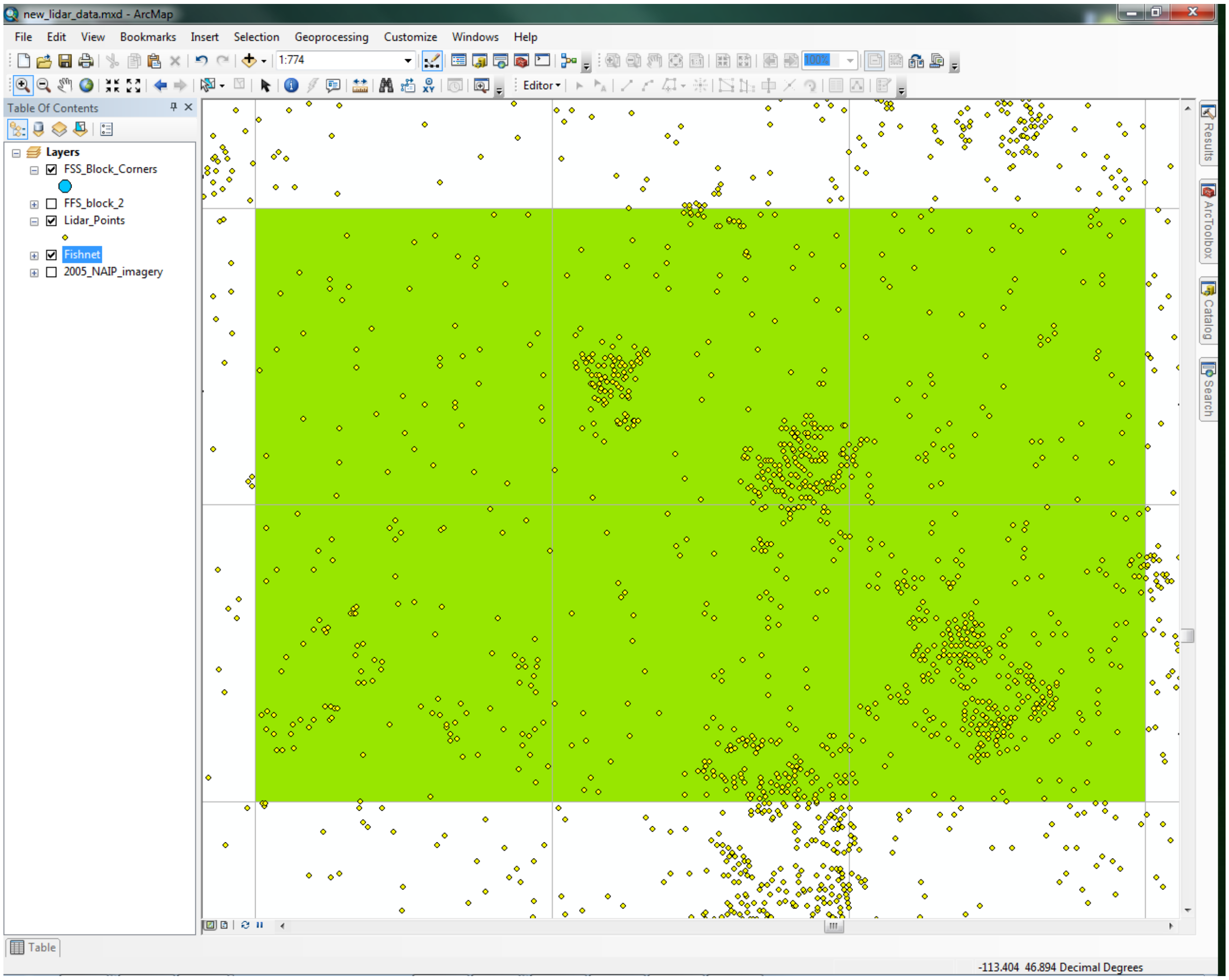

Figure 11. Overhead perspective of LiDAR derived stem map data, shown in ArcGIS. A fishnet of square 1 acre areas (lines) divides the LiDAR derived stem map data into individual 1 acre areas for processing. Of these, six 1 acre areas, highlighted in green, were used to test the process. The stem mapped data represent a portion of the Lubrecht Experimental Forest Fire and Fire Surrogates field study.

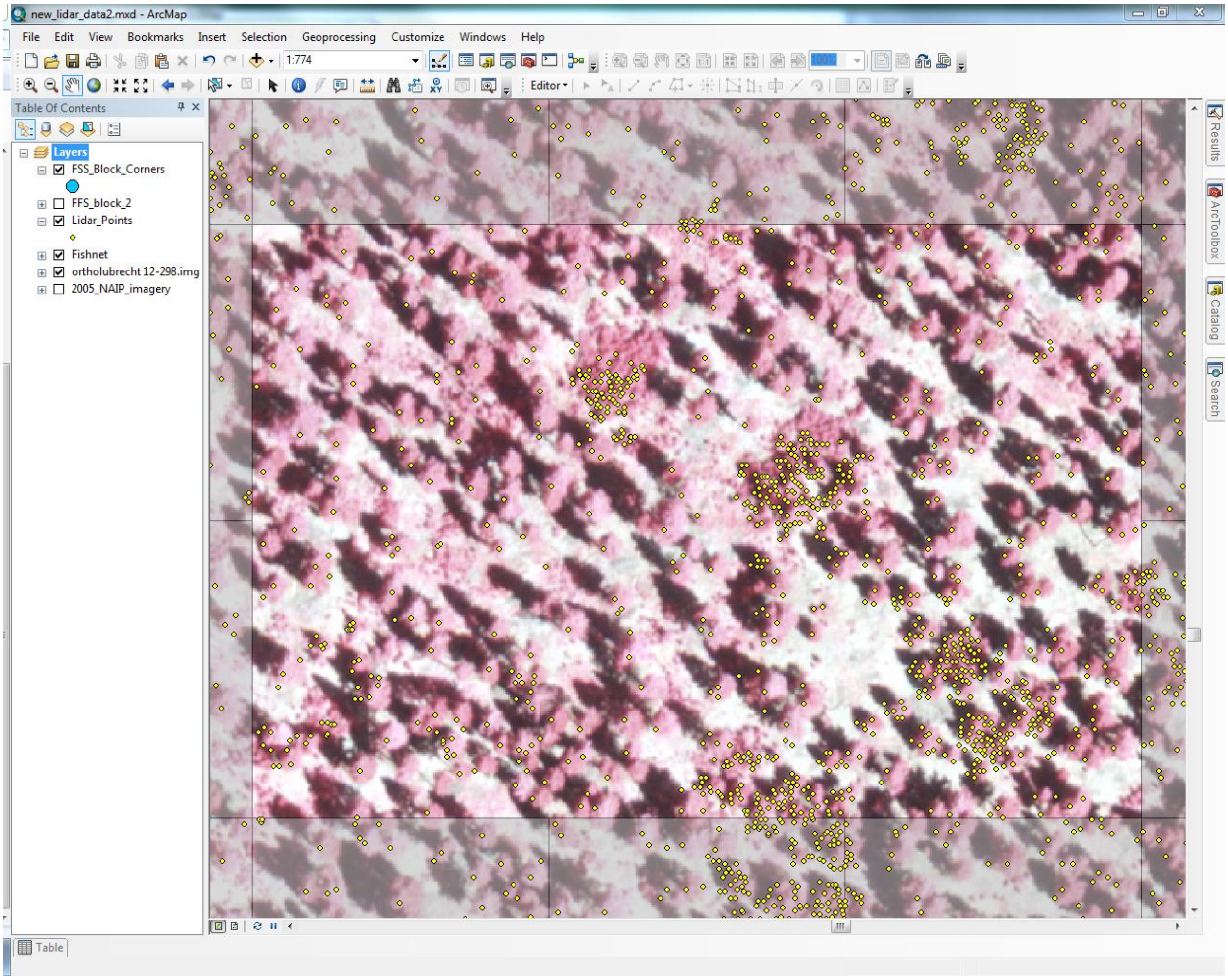

Figure 12. Overhead perspective of subset area used to test STANDFIRE process for incorporation of LiDAR derived forest fuels data, shown as an overlay with high resolution color infrared (CIR) imagery.

Within STANDFIRE, the process cycles through each one acre area, calculating canopy fuel load and associated bulk density for each tree. Canopy biomass is broken out into foliage and three size classes of branch wood, corresponding to fuel moisture time lag classes (e.g., 1 hour, 10 hour and 100 hour). STANDFIRE additionally sets a series of other fuel parameters important to the physics-based fire behavior models, such as surface area to volume ratio, heat of combustion, ash content etc. STANDFIRE provides an interactive 3D interface for examining the data (Figure 13, overhead perspective and Figure 14, oblique perspective) as well as a number of additional capabilities for spatially explicit fuel treatments and other actions.

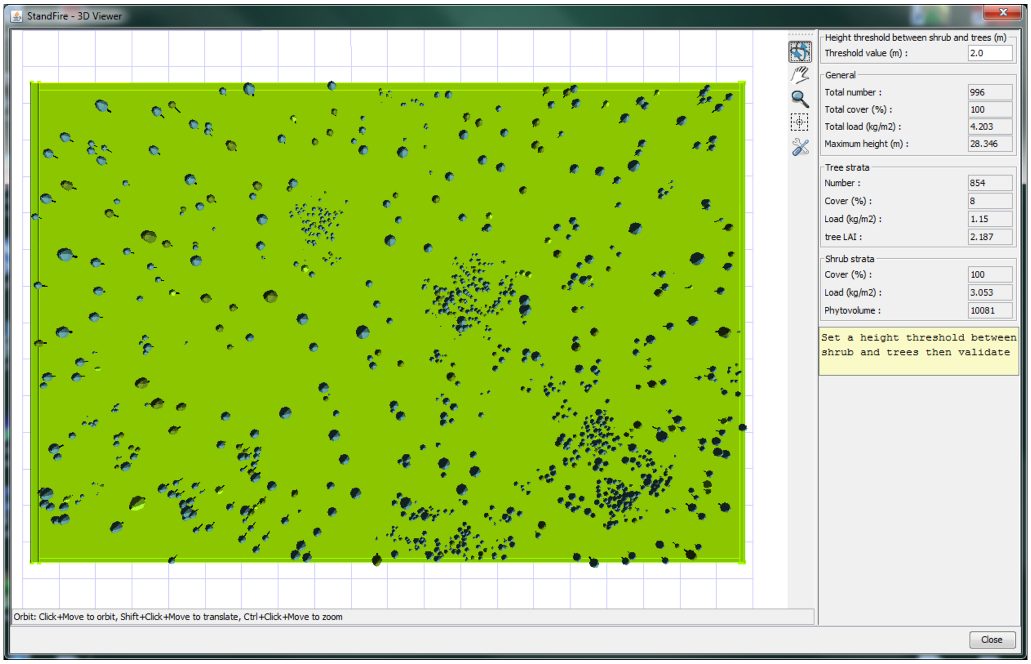

Figure 13. Overhead perspective of six acre area used to test the STANDFIRE LiDAR derived forest fuels process, shown in the STANDFIRE 3D viewer.

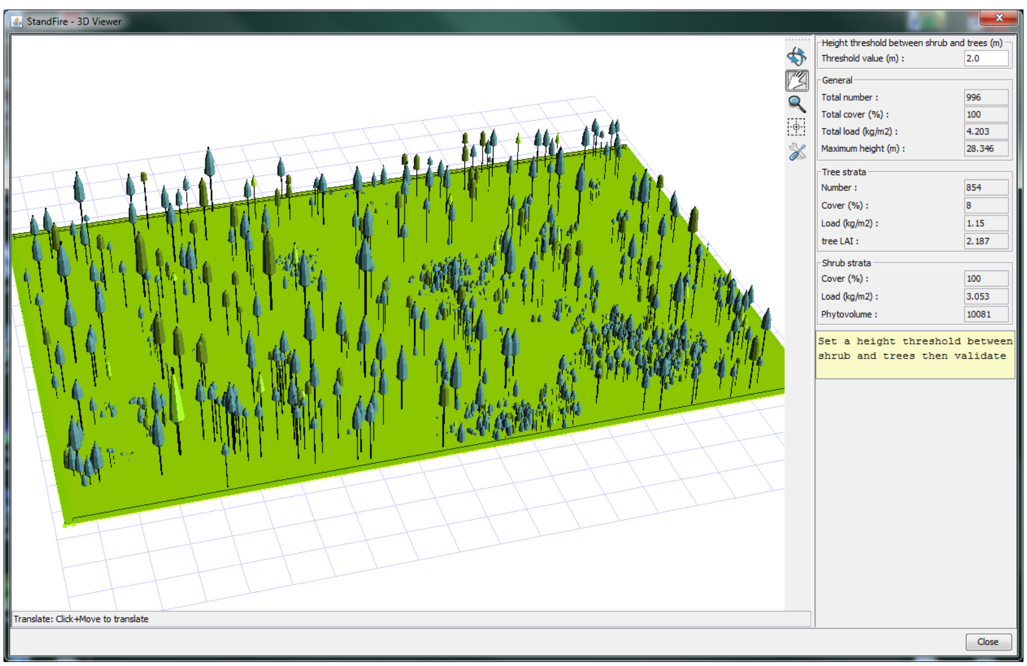

Figure 14. Oblique perspective of six acre area used to test STANDFIRE LiDAR derived fuels process, shown in the interactive STANDFIRE 3D viewer.

After fuels are modeled, they are exported to file formats appropriate for input to physics-based fire models. A key strength of STANDFIRE is that the exact same fuels inputs can be developed for both WFDS and FIRETEC, providing an unprecedented opportunity for model evaluation through direct comparison. In the future, other fire behavior model input formats will likely be developed as well in STANDFIRE.

4.5 Case Study Implications for FASMEE

The preceding set of case study results exemplify novel methods that build upon previous research (e.g., Skowronski et al. 2011, Gobakken et al. 2015) for fuel characterization based largely on point cloud data, which has important implications for FASMEE because fuels are key measures that inform all FASMEE disciplines. Fuel consumption is the primary driver of fire behavior at fine scales but also influences plume dynamics and the spatiotemporal variation in near-source smoke production at coarser scales (Parsons et al. 2011). The rate of fuel consumption determines heat release and other aspects of fire behavior, plume dynamics, and source characterization for the gaseous and particulate composition of smoke emissions. Therefore, the spatial configuration of fuel combustion and how combustion changes from the flaming front passage to residual smoldering is critical for the evaluation of many fire behavior and smoke production and dispersion models.

The FASMEE Phase I Fuel and Consumption discipline team recommended four main subtasks for observations, organized by measurement platform in Figure 15.

1) Ground-based
2) Tower or tethered balloon
3) Unmanned Aircraft Systems (UAS)
4) Airborne

4.6 Sampling Design (multi-scaled pre- and post-fire fuels mapping framework)

To spatially characterize pre- and post-fire fuel mass, volume, and bulk density as three-dimensional grids, a multi-scale fuel measurement and modeling framework is proposed. Remotely sensed point cloud data will be integrated with traditional field sampling methods (Figure 16). The density and extent of the point cloud and ground-based measurements are contingent on fuel type and structure. In general, sites with fine surface fuel beds that vary at sub-meter scales (common in southeastern US sites) can be characterized at high resolution ($\leq$ 1 m), whereas sites with fuel elements that vary at the scale of individual trees, which commonly occurs in the western US mixed conifer sites, can be characterized at coarser resolution ($\geq$ 1 m). Across all FASMEE sites, overstory tree crown structure should be mapped using airborne LiDAR immediately pre- and post-fire.

In particular, FASMEE requires high-resolution maps of fuel consumption and that the spatial configuration of pre- and post-fire fuels is coordinated with spatial and temporal characterization of fire progression, energy flux and smoke production. The rate of fuel consumption per area relates more directly to combustion than fuel load, and consumption by combustion phase varies greatly by fuel component. Thus, 3D maps of fuel consumption by component will provide more direct relationships to energy flux and emissions than maps of fuel loads and type.

Characterizing the type of fuels and spatial position of fuels relative to fireline progression will identify the sources of flaming and smoldering consumption. For example, coarse wood and duff on site would be expected to contribute most to short- and long-term smoldering. Coupled infrared measurements with mapped fuels will be used to coordinate fire behavior observations with mapped pre- and post-fire fuels. A less desirable but useful alternative are gridded maps of fuel loading and type linked to models such as CONSUME (Prichard et al. 2005) or FOFEM (Lutes et al. 2012).

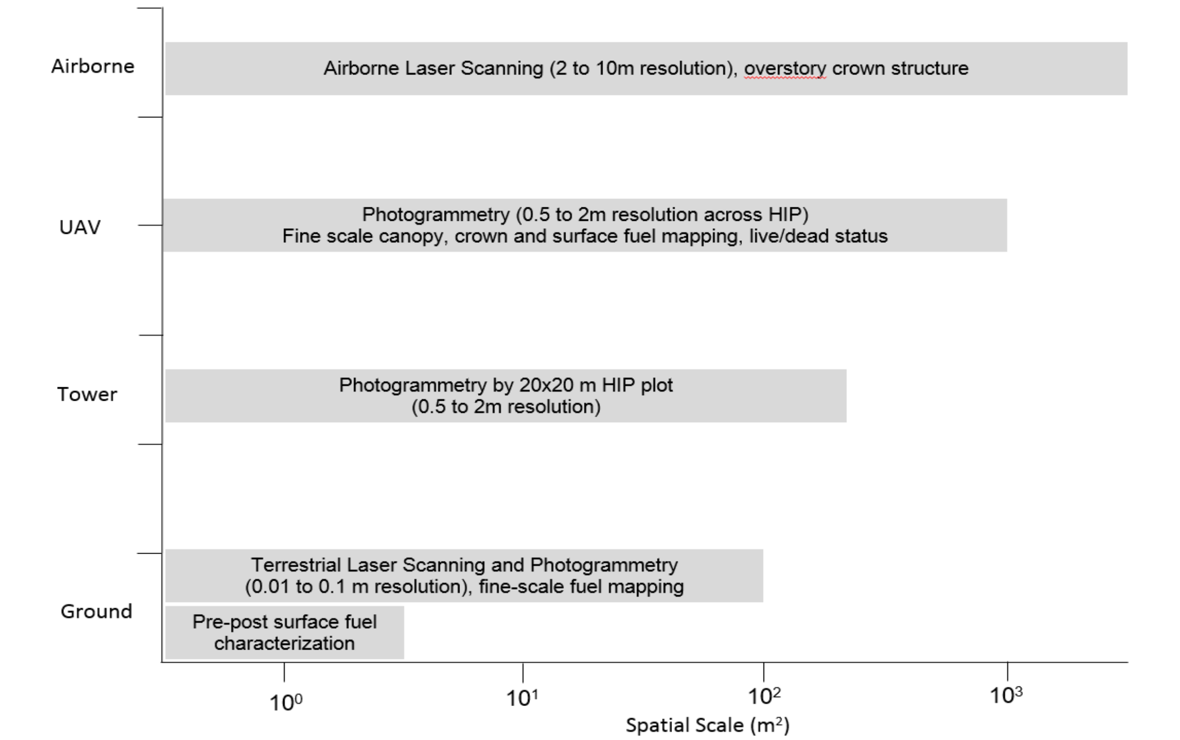

Figure 15. Hierarchical sampling scales of fuels, from ground to airborne measurements.

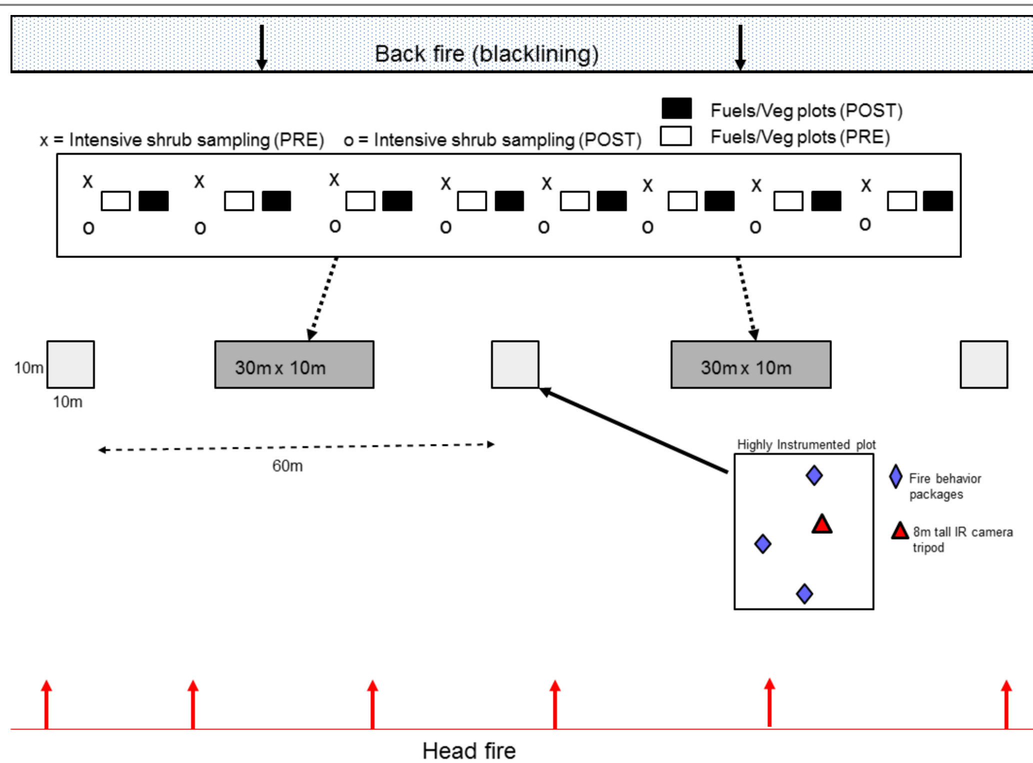

Figure 16. Schematic of 10 m x 10 m highly instrumented plots (HIPs) interspersed by destructive sampling areas to characterize fuel and consumption in southeastern surface fuel beds. Pre- and post-fire clip plots are paired and within destructive sampling areas to avoid trampling in or around the HIPs.

4.7 Justification of sampling methods

At the scale of FASMEE experimental burns, fuel consumption must be inferred by comparing pre- and post-burn fuel loads, as proposed for every fuel component in Table 1. To estimate fuel consumption in a spatially explicit manner requires that pre- and post-burn fuels measurements be collected non-destructively. This approach has been demonstrated as feasible in the New Jersey pine barrens burned with prescribed crown fires (Mueller et al. 2016), where the overstory forest canopy was characterized with pre- and post-fire ALS , and at a finer scale with TLS of forest understory vegetation burned with prescribed surface fires in a longleaf pine ecosystem (Rowell et al. 2016). Fuel measurements at both crown and surface fires are therefore included among the suite of fuels measurements detailed in Table 1.

These point cloud datasets collected via active remote sensing should be augmented with (1) complementary point cloud measurements, (2) stereo photogrammetric points collected with digital cameras mounted on UAS, to bridge the scaling gap between ALS and TLS scales, and (3) close-range stereo photogrammetry (Bright et al. 2016), to characterize destructive sample plots of ground cover and debris prior to harvesting. The classification and mapping of fuel type cannot be adequately estimated using point-cloud based techniques alone. Therefore, multi- (or hyper-) spectral image data collections, across the same nested, multi-scale framework as the point cloud data collections are desirable. The digital, passive optical imagery from which photogrammetric point clouds are derived, collected hierarchically using airborne, UAS, ground-based or handheld systems (e.g., Faro Freestyle), may suffice for this purpose.

The spatial structure of fuel beds and distribution of fuel components are so inherently complex (Keane et al. 2012; Keane and Gray 2013; Hiers et al. 2009; Loudermilk et al. 2009) that spatially explicit measurements must be relied on to characterize them (Table 1). Complementary destructive sampling is needed to predict mass of fuel loads or consumption from metrics derived from the various point cloud datasets. Destructive sampling is also needed to estimate those fuel components that are not amenable to point cloud characterization because of limited visibility, but that all contribute differently to emissions (e.g., litter, duff, and fine woody debris fractions).

Fuel consumption estimates ideally need to meet the fine-scale resolution requirements of the physically based fire behavior models. Fuel consumption estimates are also needed for smoke models, but these can be at coarser resolutions. As such, fuel consumption estimates may be aggregated to coarser resolutions to improve the accuracy of the smoke models, along with measures of spatial variability. Newer, less intensive techniques to more quickly estimate fuel load components, such as the photoload method (Keane and Dickinson 2007), may relate poorly to destructive fuel sampling methods (Volkova et al. 2016); these need to be tested in a rigorous sampling framework. However, the photoload method may suffice for informing smoke models because of the coarser-scale input requirements.

To estimate fuel moisture dynamics by fuel type across the burn units, repeated and synoptic thermal infrared or microwave measurements sensitive to dynamic fuel moistures are needed, together with contemporaneous fuel moisture samples collected on the ground and integrated into the models. Such data should be collected not just immediately before the prescribed fires, but perhaps also for a week or more preceding the fires, along with meteorological observations to capture fuel moisture dynamics at hourly to monthly time scales.

4.7.1 Ground-based measurements

Table 1: Observational specifications for the ground-based sampling.

Instrument / Technique	Spatiotemporal scales	Observation	Additional Specifications and derived parameters
Photoload plot (non-destructive)	1 m^2 micro-plot 30 per burn unit 20 per HIP	Pre- and post-fire herbaceous, low shrub, downed wood by size class (1-hr in 0-2mm, 2-4mm, 4-6mm, 10-hr and 100-hr) in kg/m^2	Located at pre- and post-burn clip plot locations, and excluding other plots at the HIPs
Photoload plot (non-destructive)	0.02-ha 4 per fuel condition 4 per HIP	Pre- and post-fire ≥1000-hr downed wood in kg/m^2	Fuel condition sampled by stratified systematic design.
Wire log method for coarse wood consumption (non-destructive)	0.02-ha 10m transects	Coupled pre- and post-measures to estimate ≥1000-hr downed wood consumption by decay class (sound and rotten)	Large logs and stumps randomly selected within inventory plots at HIPs
Forest inventory plot and subplots, transects (non-destructive)	0.02-ha 0.01-ha 1 m^2 micro-plots	Pre- and post-fire forest inventory plot measures, including trees (live and dead), saplings, shrubs, herbaceous, 1000-hr, 100-hr, 10-hr, 1-hr, 0.1-hr, litter and duff	Canopy, crown, and surface fuel load component bulk densities (kg/m^3) Compare to and validate with complimentary destructive measurements
Pre- and post-burn clip plots to estimate fuel load (destructive)	1 m^2 30 per burn unit 20 per HIP	Pre- and post-burn biomass and bulk density (kg/m^3) by fuel type and size class Physical fuel properties by fuel type, category and status (live/dead) Surface area/volume ratio Bulk density in kg/m^3, packing ratio	Fuel types include shrubs, grasses, fine wood by size class, coarse wood (sound and rotten), litter, and duff Validate corresponding non-destructive measurements. Burn unit plots located with stratified systematic sampling, excluding other plots at the HIPs

Fuel moisture	Day-of-burn grab samples of fuel components	Gravimetric water content (%) of fuel components	Fuel types include shrubs, grasses, fine wood by size class, coarse wood (sound and rotten), litter, and duff

4.7.2 Tower or tethered balloon measurements

Table 2: Observational specifications for mid-scale tower or tethered balloon sampling

Instrument / Technique	Spatiotemporal scales	Observation	Additional Specifications and derived parameters
Photogrammetry	Across HIP 0-5 to 2m resolution	Photogrammetric point clouds, pre- and post-fire	Intermediate scale 3D canopy and surface fuel mapping Fuel load, type and status (L,D)
TLS (terrestrial laser scanner)	1-100cm resolution	LiDAR point clouds, pre- and post-fire	Fine-scale 3-D canopy crown, ladder and surface fuel mapping Shrub and herb bulk density
Photogrammetry	1-10cm resolution	Surface fuel density Fuel type and status Pre- and post-fire	Co-located with ground-based fuel sampling microplots

4.7.3 UAS measurements

Table 3: Observational specifications for mid-scale UAS sampling

Instrument / Technique	Spatiotemporal scales	Observation	Additional Specifications and derived parameters
Structure-from-motion photogrammetry	Across HIP 0-5 to 2m resolution	Photogrammetric point clouds, pre- and post-fire	Intermediate scale 3D canopy and surface fuel mapping Fuel type and status (L,D)

4.7.4 Airborne measurements

Table 4: Observational specifications for airborne sampling.

Instrument / Technique	Spatiotemporal scales	Observation	Additional Specifications and derived parameters
ALS (airborne laser scanner)	Across burn unit, 3-5m resolution ≥ 8 /m^2 point density, pre- and post-fire	LiDAR point cloud characterization of fuel load, pre- and post-fire	Synoptic 3D canopy and crown fuel mapping including CBD as calibrated by ground measures
Multi-spectral (MS) imagery	Across burn unit, 1-5m resolution, pre- and post-fire	High resolution, MS characterization of fuel type pre- and post-fire	Synoptic, overhead imagery of canopy, crown, and surface fuel types as calibrated by ground measures
Thermal IR or microwave imagery	Across burn unit, pre-fire and in concert with background meteorological measurements	Synoptic measures of fuel moisture dynamics in relation to weather data over a representative period immediately preceding the fire	Coarser scale synoptic satellite observations also relevant; vegetation fuel moisture dynamics as calibrated by ground measures

V. Conclusions

The optimal configuration between ground-based, UAV, and airborne data collection systems varies substantially by site. Only by applying a strategic sampling scheme can some important fuel components (e.g., litter, duff, and woody debris) be reliably estimated at the unit level. Remotely sensed point-cloud data from airborne LiDAR or photogrammetry are, at best, only weakly sensitive to surface fuels such as litter, duff and downed wood. Smaller-scale sampling using terrestrial LiDAR or hand-held scanners are in research and development stages and in the future may allow for non-destructive sampling of these fuel components. Until that time, estimation of surface fuel components will necessarily rely on traditional field sampling methods including a combination of destructive and non-destructive sampling methods. Characterizing all fuel components that can consume is critical for emissions source characterization and in particular, can enable partitioning combustion into flaming, short-term smoldering and residual smoldering phases.

In a spatial context, it is important to oversample variation in fuel pattern relative to the spatial scale of fire behavior and effects. Upon aggregation of fine-scale fuel measures, relative regions of homogeneity (i.e., patches) emerge. For example, if a 3D, gridded fuels input layer to a physics-based fire model such as FIRETEC or WFDS captures strong gradients in fuel loads related to patchiness, then we could expect the fire intensity predicted by the model to display a similar spatial structure. If not, we would know the model isn't representing reality. In contrast, fuel maps that are truly homogeneous would result in predicted fire behavior that also appears homogeneous upon averaging multiple simulations.

Because fire and smoke modeling is intrinsically tied to accurate characterization of fuels and fire dynamics, we need consistent and co-located measures for model evaluation and development. To date, few comprehensive datasets exist that include spatially explicit fuel characterization, fire-atmosphere interactions to smoke dispersion and chemistry. We anticipate that in the short term, fuel and consumption datasets will be used to evaluate operational and next-generation fire and smoke models. The substantial investment in spatially and temporally integrated measurements of fuels, consumption, fire behavior, plume dynamics and smoke chemistry are being made to provide evaluation datasets for next-generation models. Over the next decade, these coordinated measurements will be used to not only develop and improve computationally intensive models such as coupled-fire atmosphere dynamics models but also result in improvements to operational models. For example, the Interagency Fuel Treatment Decision Support System (JFSP 2009) was originally developed to provide an integrated, web-based system for fuel treatment planning that employed common operational fire and fuel consumption models. Recently, STANDFIRE (Parsons et al. 2016), was developed as a module within IFT-DSS to support creation of 3D fuels from tree list data developed within the Forest Vegetation Simulator and run FIRETEC and WFDS to evaluate consequences of forest thinning and fuel reduction treatments on predicted fire behavior. Both programs – IFTDSS and the STANDFIRE module-- are still under development and could benefit from FASMEE evaluation datasets.

VI. Relationship to Other Findings and Ongoing Work (1-2 pages)

6.1 Surface Fuels - Southeast

Three-dimensional fuels characterization using TLS-based fuels products is an integral part of describing fuels explicitly and accurately. Descriptions of fine-scale fuelbeds as fuel load and specifically partitioned to fuel type allow for CFD to assess differential rates combustion per fuel type and coupled with fuel moisture and ambient temperature. Fuelbed products derived from TLS provide detailed spatial data that include fuel mass, height, and occupied volume. Yet, these data are difficult to segment into discrete fuel types that are critical for determining how fire will advance over a landscape. The integration of simulated fuelbeds begins to describe how fuel types are distributed at incredibly fine scales, as well as account for fuel mass not seen by the laser. The combination of these two techniques provides a logic to discretize mass by fuel type that has implications in regards to fire behavior, smoke production, and fire effects. Additionally, these estimates of fuel mass are systematic and when linked to ALS surface metrics, can be easily extrapolated over a landscape. Modeled estimates fuel mass using ALS metrics and TLS fuel mass are represented as a total fuel load for a 25 m^2, which ultimately represents variability across the fuelbed that is of value to CFD models as an input. The RxCADRE experimented highlighted the need for more robust data that characterized the measured distributions of fuel mass and type three-dimensionally. Specifically, Rowell *et al*. (2016) identified the complexity of relating TLS and field-based fuelbed heights, specifically mean heights. We see opportunities for improving field data to be collected in ways that support better three dimensional comparison with TLS data. The multi-scale nature of TLS and ALS data products are also well aligned for use in CFD models. Aggregated products to coarse scale (5m x 5m pixels) are optimal for landscape modeling in FIRETEC and TLS fuel characterizations (<1 m) also may be used for sub-grid modeling in both WFDS and FIRETEC.

6.2 Canopy Fuels – Northwest

Segmentation of ALS point clouds into discrete stems that can be ported into useable inputs for CFD models is critical to realistically distributing canopy fuels. The results presented demonstrate that rational estimations of individual trees representing multiple strata of forested systems can be produced. Integration into STANDFIRE via FFE-FVS provides a spatially explicit and detailed distributions of canopy fuels allocated by type and mass. STANDFIRE provides a number of approaches for analyzing fuels as well as the critical capability of simulating fire in two independent physics-based fire models. The capability developed in this project of providing a systematic approach for building 3D fuels inputs for physics models based on LiDAR and other fuel sampling efforts is a very important step toward model evaluation efforts. This work may also potentially lead to improved sampling strategies both for fuels and for fire behavior observations.

6.3 STANDFIRE for Modeling Hierarchical Fuels

STANDFIRE provides a broad suite of approaches for modeling wildland fuels. A number of these approaches are demonstrated in a recent paper (Pimont et al 2016), which describes FuelManager, a system developed for European fuels. Both systems are modules in, and build upon, the common architecture of the CAPSIS (Computed Aided Projection of Strategies in Silviculture) platform (http://www.inra.fr/capsis; Dufour-Kowalski *et al.* 2012). This is an integrated modeling framework for forestry research enables fuels data from various sources to be used as inputs to physics-based fire models. More information on CAPSIS is available at http://capsis.cirad.fr/capsis/home.The STANDFIRE and FuelManager modules rely on the *Fire* library, which enables simulation of fuel treatments and calculation of fire effects. More information about the *Fire* library is available at http://capsis.cirad.fr/capsis/help_en/firelib. In brief, the *Fire* library is a computer code library which represents wildland fuels as spatially-explicit 3D objects. Different kinds of vegetation are represented either as *Plants* (with specific coordinates and dimensions, typically used for trees or large shrubs) or as collections of plants called *LayerSets*. The Plants and LayerSets can include multiple types of particles, finer scale fuel elements, such as leaves, needles and twigs of various sizes, either live or dead, and characterized by their mass to volume ratio, surface area to volume ratio and moisture content. This modeling architecture provides a flexible and powerful way to realistically incorporate canopy and surface fuels measured or mapped with various approaches in the context of FASMEE or other similar projects.

6.4 Management Implications

In many fire-prone ecosystems, combined impacts of climate change, fire exclusion, and rapid development of the wildland urban interface create complex management issues for fuel and fire managers. Managers increasingly need more accurate and precise fuels maps to prioritize fuel reduction treatments and ecosystem restoration. Fuel maps created from both traditional and 3D point cloud datasets will constitute the next generation of planning products for managers that this research will bring closer to operational utility, to be applied towards, for example, planning fuel breaks or fire interactions in the wildland-urban interface.

The proliferation of ALS data sets across the United States means that managers should expect improved fuel estimates and spatial data products. The techniques outlined for FASMEE phase 1 will greatly improve fuel characterization and ultimately capture more variability on the landscape that affect decision making in forest planning, fuels management, and fire management. The ability to map and assign discrete mass to individual trees also allows for managers to better relate structural components of forests that support theories as the ecology of fuels (Mitchel *et al.* 2009), where dominant pine stands produce fuel continuity that affect understory plant diversity and hardwood regeneration in the SE.

Although FASMEE fire and fuel consumption observations will be first used in model evaluation and development, the public will ultimately benefit from this research. To address the complexity of future wildland fire management issues, we need an improved understanding of fuel-fire relationships. As we are armed with more accurate and precise fuel maps and fire and weather models, we can better forecast fire intensities and fire behavior dynamics that threaten or endanger people, their property, and the natural resources that land managers are charged to protect.

VII. Future work needed (1-2 pages)

The research described in this report is fundamental to FASMEE, but all of the pieces of the concept diagram at the start of the report have not been unified for an operational burn support. Given the availability of the RxCADRE datasets, greater focus thus far has been in the SE, but we also investigated canopy/crown fuels representative of western conifer systems.

Figure 17. Valentijn Hoff piloting a quadcopter UAS.

In the domain of fine-scale fuels characterization, we have begun testing other methods of data collection that compliment and expand our ability to characterize increasingly larger areas in a landscape. We have begun to use UAS (Figure 17) to produce point clouds from structure for motion and employ hand-held laser scanners that are mobile and less expensive than traditional TLS systems. We have conducted field experiments in the SE where all modes of data are collected to begin building models that link fuel classification and mass predictions. We also leveraged other projects to test new technology and sites. We used a RIEGL VZ-2000 laser scanner, which has a maximum sampling rate of 1000 kHz and range of up to kilometer. We tested this laser in spruce\fir systems of the north rim of the Grand Canyon as a proxy for the Fish Lake FASMEE site.

We have also utilized lessons learned from previous campaigns to create a new 3-D fuel sampling method (Figure 18). This method collects fuels data as a volume characterizing fuels by height strata and fuel type per 10 x 10 cm voxel cells. We also collect biomass by 10 cm strata and randomly subsample by 10 x 10cm individual cells to ascertain biomass distributions by strata and variability within strata. We believe this method of fuels collection will better support analysis of TLS point clouds and voxel products.

Figure 18. Louise Loudermilk and Christie Hawley destructively sampling 3D fuels in 10 cm voxels.

Additional work in forested systems is needed where surface fuel beds are often obscured by canopy. This study found that simulations using established allometries to produce simulated forests found that canopy height is not a significant predictor of biomass, but modeling forest profiles that estimate plant area fractions improved LiDAR-derived estimates of forest biomass.

The ability to produce realistic simulated laser point clouds is a significant proving mechanism for understanding how terrestrial laser scanners characterize fine fuels. Previous attempts at describing these fuels have been difficult due to occlusion and point sampling variability using terrestrial laser scanner data collected obliquely from a boom lift (Rowell *et al.* 2016). Further work needs to be conducted to determine how well biomass estimated from the simulated fuelbed performs specifically integrating more intensely sampled fuelbeds. Automation of fuelbed construction is also imperative to reducing variability and subjectivity. We also foresee benefits for the integration of these findings with other high resolution simulation techniques, such as FUEL3D (Parsons et al. 2011), where we may begin to combine surface and canopy fuels for improved inputs used for physics-based fire behavior models.

VIII. Deliverables crosswalk (and additional deliverables)

Table 5: Project deliverables

Deliverable	Description	Date
Project kick-off meeting	Participated in a 2-day planning retreat, Seattle	April 2016
SE reconnaissance field work	Participated in a field tour of the SRS and Ft Stewart	May 2016
SW reconnaissance field work	Participated in a field tour of the Fishlake and Kaibab/N Rim study sites	July 2016
SW preliminary field sampling	Conducted traditional fuel sampling at the Fish Lake site, and at Kaibab/N Rim from newly collected TLS and existing ALS data	Oct 2016
Observational study design	Contributed to the FASMEE Study Plan, the main deliverable of Phase I.	March 2017
SE TLS-based surface fuel modeling	Predicted surface pre- and post-fire fuel loads and estimated surface fuel consumption from TLS metrics, using RxCADRE datasets as a case study	May 2017
SE TLS-ALS integration	Upscaled TLS-based fuel predictions to burn unit level from ALS metrics, using RxCADRE datasets as a case study	May 2017
SW ALS-based canopy fuel modeling	3D fuel modeling of canopy/crown fuels with STANDFIRE	May 2017
FASMEE Background Paper	Review paper on background research that informed FASMEE and future research needs. Susan Prichard, co-lead, is lead author.	In preparation
JFSP Final Report	Final report (this document)	June 2017

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