FINAL REPORT

Title: Evaluating canopy fuels across multiple spatial scales for improved fire modeling

JFSP PROJECT ID: 20-1-01-20

December 2021

Lisa Patrick Bentley
Sonoma State University, Department of Biology

Brieanne Forbes
Sonoma State University, Department of Biology

Evaluating canopy fuels across multiple spatial scales for improved fire modeling

Table of Contents

List of Tables

List of Figures

List of Abbreviations/Acronyms

Acronym	Meaning
ALS	Airborne LiDAR Scanner
CBH	Canopy Base Height
DEM	Digital Elevation Model
GLM	Generalized Linear Model
HMLS	Handheld-Mobile Laser Scanner
LiDAR	Light Detection and Ranging
RdNBR	Relativized delta Normalized Burn Ratio
SfM	Structure from Motion
TIN	Triangulated Irregular Network
TLS	Terrestrial Laser Scanner
UAS	Unoccupied Aerial System

Keywords

ladder fuels, terrestrial laser scanner (TLS), handheld-mobile laser scanner (HMLS), unoccupied aerial system (UAS), airborne laser scanner (ALS), Structure from Motion (SfM), wildfire burn severity

Acknowledgements

We thank students in SSU's Research Experience in Biology class from Fall 2020: Christopher Aguilar, Eloisa Burke, Stef Delgado, Mia Furman, Angeline Gorenflo, Shannon Manhoso, Frida Pereira, Rosa Ramirez and undergraduate researchers Sarah Arroyo-Chavez, Jolene Markarian, and Lauren Webster for their analysis of photo banner data. We are grateful to Daniel Crocker for his assistance with statistical analyses and to Tadashi Moody and Sean Place for their thoughtful comments on the manuscript. We appreciate the hard work of the 3DForests field crew for data collection including Elise Piazza and Catherine Seel. We additionally thank the Ag and Open Space District and Pepperwood Preserve for granting us access to their sites and facilitating our research data collection.

Abstract

While fire is an important ecological process in the western United States, wildfire size and severity have increased over recent decades as a result of climate change, historical fire suppression, and lack of adequate fuels management. Due to the urgency to build ecosystem resilience and protect life and property, land managers implement fuel management programs. Technology used to quantify ladder fuels, which bridge the gap between the surface and canopy, and lead to more severe canopy fires, can inform management treatments to reduce future wildfire risk. In this study, we evaluated several remote sensing techniques and field measurements to quantify ladder fuels and related ladder fuel metrics to wildfire burn severity. Ladder fuel data at 1-m strata from 1-8 m were collected using a photo banner, a terrestrial laser scanner (TLS), a handheld-mobile laser scanner (HMLS), an unoccupied aerial system (UAS) with a multispectral camera and Structure from Motion (SfM) processing (UAS-SfM), and an airborne laser scanner (ALS) in 35 plots in oak woodlands in Sonoma County, California, USA prior to the occurrence of natural wildfires. Canopy base height (CBH) was estimated in the field, and post-wildfire burn severity was calculated using the Relativized delta Normalized Burn Ratio (RdNBR). The linear relationships between ladder fuel metrics at each stratum collected via different methods were compared using Pearson's correlation (r) and RdNBR prediction via ladder fuel estimation was evaluated with a generalized linear model (GLM). All methods were not consistently related to each other, unless CBH class was included as a means of categorizing structural differences among plots. The UAS-SfM approach often could not produce measurements below 8 m due to lack of below-canopy detection, and, therefore, is highly limited for ladder fuels estimation in oak woodland and mixed conifer forests. The most common ladder fuels strata included in the burn severity model were 1-2 m and 3-4 m. The most predictive models included data from TLS and ALS with R^2 of 0.67 and 0.66, respectively. By accounting for interactions between ladder fuels, CBH, and burn severity, diverse remote sensing approaches can be used to estimate and validate ladder fuels.

Objectives

Our original study objectives were to: 1) Determine if the calculated relative ladder fuel cover metric derived from airborne LiDAR is similar to measurements of ladder fuels calculating using the Kramer et al. (2016) photographic method and using a terrestrial laser scanner (Hillman et al.2019). 2) Derive the relative ladder fuel cover metric using 2 different types of terrestrial LiDAR acquisition systems (Riegl and Zeb). 3) Relate the relative ladder fuel cover metric (calculated via photos, ALS and TLS) to canopy base height (calculated via ground measurements, ALS and TLS). These objectives directly used science to inform resource management by providing a quantitative evaluation of methods currently being used to estimate canopy fire fuels. They also helped to provide a recommendation to land managers for future measurements to be taken, with respect to both metric and equipment to be used.

An additional remote sensing technique was included in this project due to its relevance - an unoccupied aerial system with Structure from Motion processing (UAS-SfM). While objectives 1 and 2 were met, the direction of the question changed slightly. Objective 3 was partially met with the inclusion of CBH in our models, however it was not estimated via ALS or TLS due to complications related to their differences in resolution. A unique opportunity arose when two of our study sites were burned by a natural wildfire immediately after taking measurements at both which led our objectives to become: 1) What is the linear relationship between ladder fuel metrics estimated using TLS, HMLS (aka Zeb), UAS, ALS, and photo banner methods, and how do these relationships change within CBH categories?; 2) For each measurement method, can ladder fuels be used to predict wildfire burn severity (i.e., RdNBR) at a plot scale? If so, which ladder fuel strata from 1-8 m is the most important predictor variable?; and, 3) When predicting burn severity, do different methods of estimating ladder fuel variables lead to different predictive capabilities? We hypothesized that ladder fuel metrics from different approaches would be correlated to each other if their measurement approach was similar (i.e., terrestrial or airborne perspectives, laser or image based). In addition, we hypothesized that TLS and HMLS data would most accurately predict burn severity (RdNBR) due to their high point density, closely followed by ALS. We predicted UAS-SfM and the photo banner would not be able to significantly predict burn severity (RdNBR) due to the lack of below canopy detection of UAS-SfM and 4-m height limit of the banner. We hypothesized that the most important predictor ladder fuel strata would be 1-4 m, as was found by Green et al. (2020).

Background

While fire is an important ecological process in the western United States, wildfire size and severity has increased over recent decades as a result of climate change, historical fire suppression, and lack of adequate fuels management (Jolly et al. 2015, Jain et al. 2017; Abatzoglou et al., 2016; Dennison et al., 2014). Due to the urgency to build ecosystem resilience and reduce risk to life and property in light of future wildfire events, land managers are implementing fuel management programs (Duff et al., 2013, 2019; Stephens et al., 2012). Ladder fuels, which are live and dead vegetation that bridge the gap between the surface and the canopy, can potentially cause a low-severity surface fire to become a high-severity canopy fire (Ottmar et al. 2007; Menning and Stephens, 2007). Since fuels are challenging to measure in the field using traditional forestry methods, fuel structure is often estimated via remote sensing technology. Remote sensing allows for measurements across large and inaccessible areas at a potentially lower cost, depending on scale of measurements, relative to field-based techniques (Gale et al., 2021).

The use of airborne laser scanners (ALS), or LiDAR, has been used to estimate spatially explicit fuel parameters over landscape to regional scales (Jakubowksi et al., 2013; Andersen et al., 2005, Kelly and DiTommaso, 2015; González-Ferreiro et al., 2017), and can contribute to reliable and robust estimates of modeled forest fire behavior (Kelly et al., 2017). At plot to stand scales (i.e., 1 to 50 ha), unoccupied aerial systems (UAS; Joyce et al., 2021) can acquire digital aerial images at a relatively low cost; useful for repeated forest monitoring (Campbell et al., 2020). When UAS are flown to capture sufficiently overlapping images (i.e., 75-85%), Structure from Motion (SfM) data processing can generate 3D point clouds of vegetation structure, which has the potential to quantify fuel loads (UAS-SfM). At plot scales, terrestrial laser scanning (TLS), a ground-based form of LiDAR mounted on a tripod, is successful in estimating variables related to the spread of canopy fires, subtle fire-induced change, and forest fuels structural metrics (Chen et al., 2016; García et al., 2011; Gupta et al., 2015; Hillman et al., 2021), with millimeter accuracy and precision (Disney, 2019). Handheld-mobile laser scanners (HMLS), also used at plot scales, are a lightweight LiDAR option that are about 30% the cost of a TLS and have been found to accurately estimate tree heights under heights of 25 m (Hyyppä et al., 2020) and diameter at breast height (DBH) with less variation than field measurements (Chudá et al., 2020; Hyyppä et al., 2020). Currently, no studies have examined the use of HMLS to examine ladder fuels and few studies have used the technology to examine forest structure parameters (Donager et al., 2021; Marselis et al., 2016).

While there is a diversity of advanced techniques to measure forest structure, the scientific community lacks consensus on which remote sensing approach is best to estimate fuels due to the tradeoff in coverage, cost, accuracy, and efficiency between approaches. Furthermore, there is no standard for quantification of fuels across methods or comprehensive validation of fuels measured by remote sensing with on-the-ground data. As a result, fuels are often indirectly measured. For example, the upper limit of ladder fuels is defined as canopy base height (CBH), a metric that defines the distance between the bottom of the canopy and ground. Thus, CBH, a distance that influences vertical propagation of fire and is easily measured in the field or by remote sensing, is the variable most often used to model the transition of surface to crown fires, as opposed to ladder fuels (García et al., 2011).

Recently, however, Kramer et al. (2016) presented a ground-based photographic technique (referred to hereafter as the photo banner) to directly measure ladder fuels, rather than using CBH to model the effects of ladder fuels. Importantly, this explicit measure of ladder fuels was found to correlate with a ladder fuel metric developed using airborne LiDAR data (Kramer et al. 2016). Currently, land managers and conservation groups in Sonoma County, California use this ladder fuel metric via ALS measurements in machine learning models related to wildfire severity (Green et al., 2020). The higher the density of shrubs and forest ladder fuels, the higher the canopy damage was observed from wildfires (Green et al., 2020).

Given the important predictive role of ladder fuels, as estimated by ALS data, in predicting canopy damage following wildfire in Sonoma County, the purpose of this study was to evaluate the use of a suite of remote sensing approaches (TLS, HMLS, UAS-SfM, and ALS) and field measurements (photo banner) to quantify plot-scale ladder fuels in oak woodlands and mixed forests in the same region and relate measurements of ladder fuels to wildfire burn severity. We chose to define burn severity using the Relativized delta Normalized Burn Ratio (RdNBR) applied to pre- and post-fire Landsat multispectral satellite imagery (Miller and Thode, 2007).

Materials and Methods

Data collection and processing

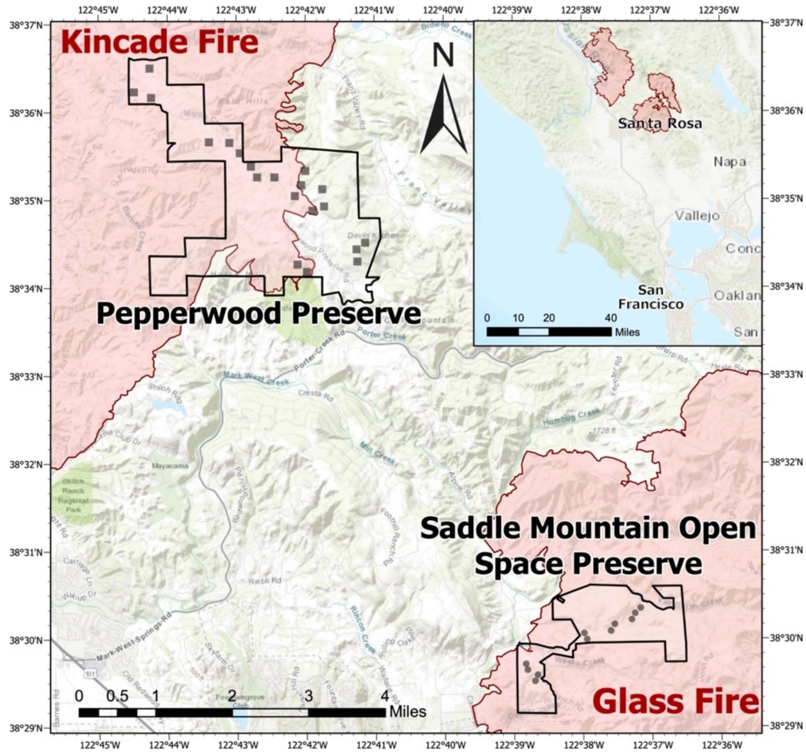


Figure 1: Map of our study locations (Pepperwood Preserve and Saddle Mountain Open Space Preserve) and plots (indicated by grey squares and circles) in Sonoma County, California. The perimeter of each wildfire that occurred during our research study is shown in red.

Data were collected from two study sites, Pepperwood Preserve (3,200 acres; 38° 34' 57.5", -122° 42' 37.3") and Saddle Mountain Open Space Preserve (960 acres; 38° 30' 3.3", -122° 37' 44.6"), both in the Mayacamas Mountains in Sonoma County 10-20 km outside of Santa Rosa, California, USA (Figure 1). The most prominent community at both sites is oak woodlands and mixed conifer forests. Data were collected at both sites immediately before a natural wildfire at each. The Kincade Fire burned 14 of our 24 plots at Pepperwood in September 2020, and the Glass Fire burned all 11 of our plots at Saddle Mountain in September 2021.

At each site, a variety of approaches were used to generate ladder fuel metrics at different height strata from 1-8 m, using the equation used by Kramer et al (2014). We adopted Kramer et al.'s

(2016) photographic approach ("photo banner") to measure ladder fuels at a plot-level. Ladder fuel banner photos were analyzed by finding the percent area of all parts of vegetation covering the photo banner via ImageJ (Kramer et al., 2016; National Institute of Health, Maryland, USA, version 1.52). Crown base height was measured for each tree >10 cm DBH in each plot. A tape measure or a laser hypsometer was used to measure from the lowest live crown to the ground when possible. To determine canopy base height (CBH), the crown base height for each tree within each plot was averaged. The CBH values were binned into four CBH categories based on the distribution of our data and were as follows: low (0 – 3m), medium (3.01 – 6m), high (6.01 – 9m), and very high (>9m).

Terrestrial laser scanner (TLS): A Riegl VZ-400i TLS (RIEGL Laser Measurement Systems GmbH) was used to scan each plot as recommended by Wilkes et al. (2017). Processing for TLS data occurred in RiSCAN PRO (Riegl Laser Measurement Systems GmbH, Horn, Austria, version 2.8.2). To align all scans within each plot to each other to create one plot-level scan, a course and fine registration. TLS plot-level data was aligned to ALS data in NAD83(2011) / UTM Zone 10N and geoid 12B for accurate georeferencing. Following registration and alignment, Lidar360 (GreenValley International, Berkeley, California, version 4.1) was used to create a DEM used to normalize each plot.

Handheld-mobile laser scanner (HMLS): We walked a GeoSLAM ZEB-Revo for 5-10 minutes throughout each plot to collect data points. The path of the HMLS was based on Bauwens et al. (2016). Using the GeoSLAM software (GeoSLAM, Nottingham, United Kingdom), HMLS data were automatically generated for each plot. The resulting point clouds were then aligned to TLS data. Lidar360 was then used to height normalize HMLS data by DEM for each plot.

Unoccupied aerial system (UAS): A SenseFly eBee X fixed-wing UAS and a DJI Matrice 200 quadcopter UAS with a MicaSense RedEdge-MX sensor were flown during the same time period that TLS, HMLS, and photo banner data were collected. For more detailed information about UAS methods see Reilly et al. (2021). Due to the accuracy of the ALS DEM, it was used to height normalize UAS-SfM data using the R lidR and raster packages.

Airborne laser scanner (ALS): ALS data were downloaded from existing data collected in 2013 for Sonoma County (QL1/2013). Data can be found at http://sonomavegmap.org/data-downloads/. For more detailed information about ALS methods see Watershed Sciences (2016). ALS ground points were used to create a 1-m raster DEM using the R lidR and raster packages and TIN interpolation and then used to height normalize the ALS point clouds.

Wildfire burn severity: Landsat 8 satellite images were used to calculate the Relativized delta Normalized Burn Ratio (RdNBR) from the Kincade and Glass fires, using formulas in Miller and Thode (2007). Plot RdNBR values were binned similarly to Miller and Thode (2007), but due to a small sample size for high severity plots (n=1), the high severity plot was grouped into a moderate and above group (316-1200).

Data Analyses

Ladder fuels: Ladder fuels were then extracted at the plot level from TLS, HMLS, UAS-SfM, and ALS data using the lidR package in R. The mean CBH (5.0 m) plus one standard deviation (2.7 m) was used to determine the maximum height for ladder fuels (8.0 m). Using the equation from Kramer et al. (2014, Table 2A), the density of points within all 1-m ladder fuel strata up to 8 m were calculated using only points above 0 m (filtering out negative points).

Comparing ladder fuel metrics across methods: Pearson's product moment correlation (r) values were used to compare ladder fuel metrics derived from each method. To compare the metrics used by Kramer et al. (2016) and Green et al. (2020) to our data, ladder fuels from 1-4 m and 1-8 m were also extracted and calculated from each dataset using Equation 4. Since the photo banner only goes up to 4 m, it was not included in any analyses above 4 m. Metrics were analyzed within CBH bins to determine if ladder fuels were related to average plot CBH (and thus, overall plot forest canopy structure). Note that for this study, CBH data were only measured in the field and not via remote sensing methods.

Modeling the relationship between ladder fuels and burn severity: To determine the effect of ladder fuels metrics on RdNBR, and interactions with CBH, linear models were selected using proc GLMSELECT in SAS (SAS Institute Inc, Cary, North Carolina, version 9.4) using forward stepwise variable selection based on minimizing Schwarz's Bayesian Criteria (SBC). The global model contained each ladder fuel strata, CBH, and the interaction between CBH and each ladder fuel strata.

Results and Discussion

Data collected by TLS, HMLS, UAS-SfM, and ALS had average plot-level point densities of 399,064 pts/m^2, 16,378 pts/m^2, 330 pts/m^2, and 17 pts/m^2, respectively. For each method, there was a high percentage of points between 0-1 m and a decrease in percentage of points between 1-2 m (Table 2). While our ladder fuel strata were between 1-8 m, we also included the point density between 0-1 m in our discussion as this measurement was included in the calculation of each ladder fuel strata. The TLS and HMLS data gradually increased in point density with decreasing strata height, due to bottom-up scanning of the forest. Out of the 84% of TLS data collected below 8 m, approximately half was between 0-1 m (Table 1; Table 2). Out of the 96.7% of HMLS data collected below 8 m, 32.5% was between 1-8 m. In contrast, point density in UAS-SfM and ALS data gradually decreased with decreasing strata height (not including 1-2 m for UAS-SfM), due to the top-down views of those sensors. Data collected using UAS-SfM had the highest point density at the top of the canopy, but the technique did not capture as many understory or ground points as TLS or HMLS. Only 13.3% of UAS-SfM data were between 1-8 m, while 28.2% were between 0-8 m. Data collected by ALS were comparatively sparse, but had better canopy penetration than UAS-SfM, with 35.9% of points between 0-8 m, 19.6% of points between 1-8 m, and an average of 2.8% of points in each stratum between 1-8 m. These patterns in the distribution of point density by measurement approach remained consistent irrespective of plot CBH classification (Figure 2).

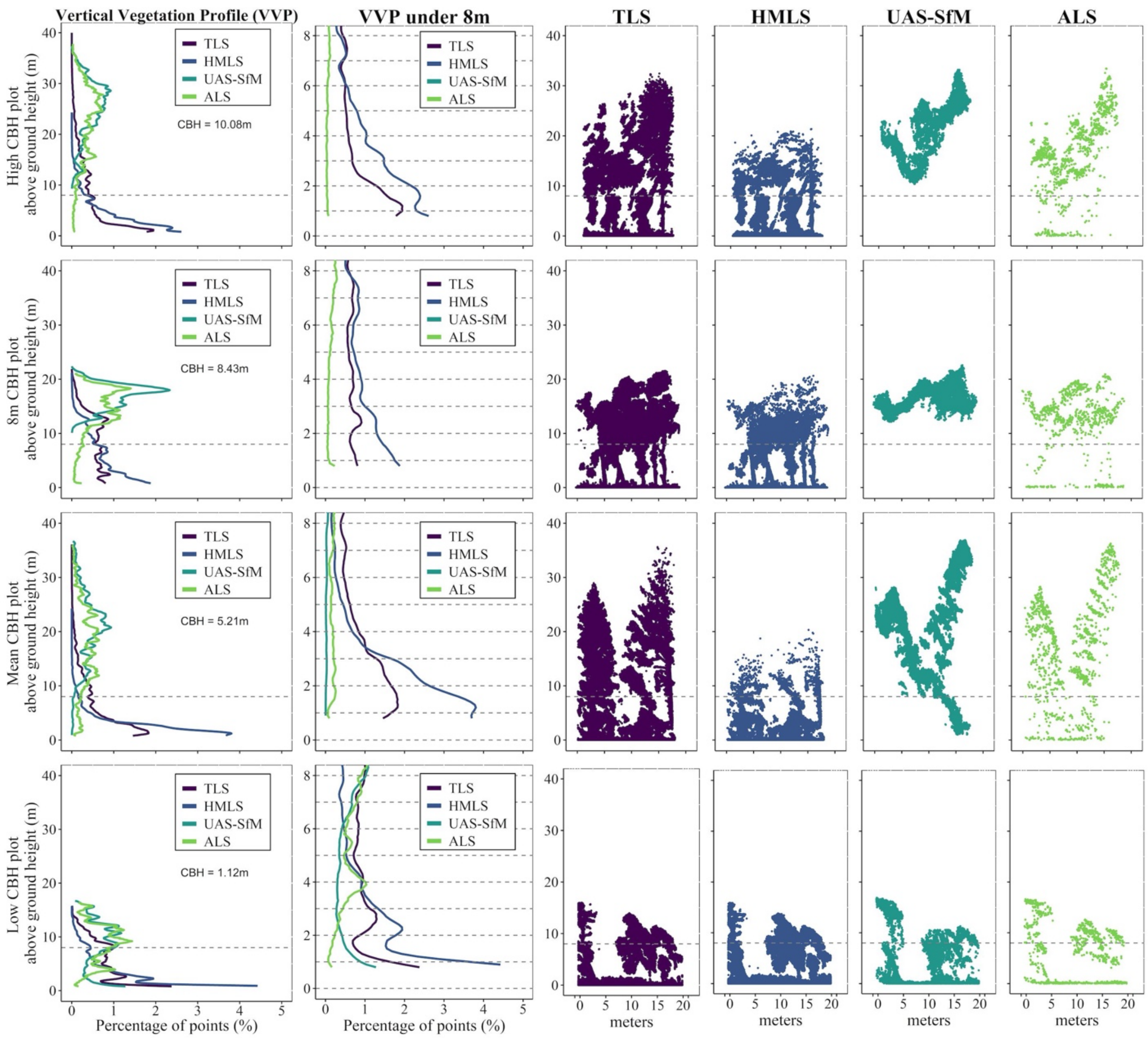


Figure 2: Vertical profile of vegetation (VVP) generated by each remote sensing method, separated into bins based on CBH for a representative plot. The percentage of points at each height was found by dividing the number of points at each height by the total number of points (above 0.5m) for each method. VVP under 8m shows the same data as the whole VVP, but zoomed in. The grey dashed line shown in the VVP represents 8m, the maximum height we used for ladder fuels, the grey dashed lines shown in the VVP under 8m, are in 1m increments and represent our ladder fuel strata.

	TLS	HMLS	UAS-SfM	ALS

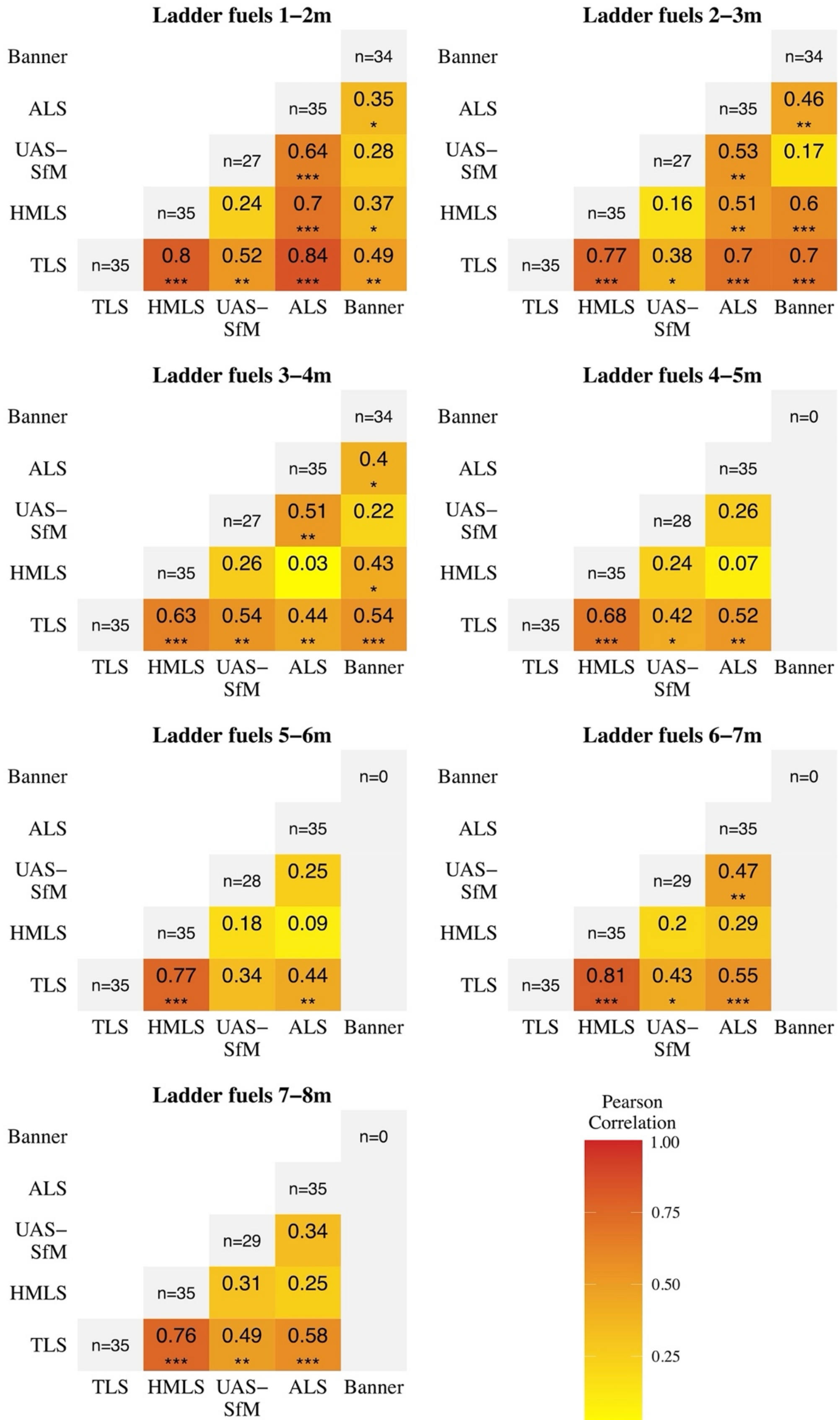
0-1m	173,788.3	10,201.52	31.74	3.20
1-2m	57,311.12	2,884.81	10.55	1.70
2-3m	61,264.81	2,088.40	10.40	1.97
3-4m	47,787.23	1,364.58	11.89	2.10
4-5m	36,910.99	899.64	11.33	2.18
5-6m	31,782.90	672.06	15.25	2.32
6-7m	27,585.26	514.63	21.13	2.31
7-8m	22,966.50	380.56	24.78	2.50

Table 1: Point density at each stratum, for each method. We included 0-1m because this data is included in the ladder fuel strata and clearly demonstrates the significant amount of data points for both the TLS and HMLS data. Point density was calculated by rasterizing the stratum. The percentage of points at each stratum was found by dividing the number of points at each stratum by the total number of points for each method.

	TLS	**HMLS**	**UAS-SfM**	**ALS**
0-1m	43.5%	64.2%	14.9%	16.3%
1-2m	10.4%	13.0%	2.4%	1.1%
2-3m	7.7%	6.8%	1.2%	1.9%
3-4m	5.9%	4.2%	1.1%	2.3%
4-5m	4.8%	2.9%	1.2%	2.7%
5-6m	4.4%	2.3%	1.7%	3.2%
6-7m	4.0%	1.9%	2.5%	3.8%
7-8m	3.5%	1.4%	3.2%	4.6%
Total 1-8m	40.7%	32.5%	13.3%	19.6%
Total 0-8m	84.2%	96.7%	28.2%	35.9%

Table 2: Percentage of points at each stratum, for each method. We included 0-1m because this data is included in the ladder fuel strata and clearly demonstrates the significant amount of data points for both the TLS and HMLS data. The percentage of points at each stratum was found by dividing the number of points at each stratum by the total number of points for each method.

Estimates of ladder fuel metrics were generated using TLS, HMLS, ALS, and photo banner methods, using sub-canopy height stratification techniques similar to other studies (Skowronski et al., 2007; Rowell et al., 2020; Kramer et al., 2016). While it was not possible to validate the ladder fuel density measured by each method in this study (i.e., through destructive sampling), our results imply that each method can be used on their own to examine a relative change in ladder fuel density over time. When comparing estimates of ladder fuels metrics across all methods, without accounting for forest canopy structure as defined by CBH, estimates from different approaches were not consistently correlated to one another (Figure 3). This finding suggests that estimating ladder fuels using point density is highly variable across methods.



Ladder fuels 1–2m
Ladder fuels 2–3m
Ladder fuels 3–4m
Ladder fuels 4–5m
Ladder fuels 5–6m
Ladder fuels 6–7m
Ladder fuels 7–8m
TLS
HMLS
UAS–SfM
ALS
Banner
Pearson Correlation
1.00
0.75
0.50
0.25
0.00

Figure 3: Heatmap of Pearson correlation coefficients to compare ladder fuel metrics at multiple strata across methods. Significance is as follows: *** p-value ≤ 0.001, ** 0.001 > p-value ≤ 0.01, * 0.01 > p-value ≤ 0.05. Note the removal of the banner from strata above 4 m.

While we found various strong relationships between methods in ladder fuel densities, the magnitude of each measurement across techniques was not the same, primarily due to differences from the top-down (ALS, UAS-SfM) or bottom-up (TLS, HMLS) view of the canopy. TLS and HMLS had relatively low penetration into the upper-canopy, with 84% and 97% of points below 8 m, respectively (Table 1; Table 2; Fig. 3), and consequently, since most of their points were sub-canopy, HMLS and TLS ladder fuels were significantly correlated across strata (+0.63 to +0.81) with percent differences from 3 to 5%. In contrast, only about a third of UAS and ALS points were below 8 m (28% and 36%, respectively), with UAS points heavily concentrated in the upper canopy or in canopy gaps (Fig. 3); and subsequently, ladder fuel correlations between UAS and ALS were generally weaker than TLS and HMLS, ranging from +0.25 to +0.64. Due to this differential detection of forest structure when sensing downward or upward, differences in the magnitude of metrics were especially pronounced for measurements of ladder fuels in the lower (1-2 m) and upper (7-8 m) strata. For example, across all plots, TLS had average estimates of ladder fuels that were 10% higher than ALS in the 1-2 m strata, whereas ALS had on average 8% more ladder fuels estimated in the 7-8 m strata. These findings corroborate other studies which have found that TLS are more sensitive to 3D structure in the lower canopy than ALS and UAS LiDAR (Brede et al., 2019; García et al., 2011; Hillman et al. 2021a; Hillman et al., 2021b; Levick et al., 2021). Thus, while patterns in metrics were correlated between sensors, variation in the ladder fuel percentage values due to top-down vs bottom-up measurement approaches, in addition to factors such as laser scan overlap, scan angles, wavelength, and power, could explain differential significance of correlations among ladder fuels in our results, and ultimately their utility in subsequent fire behavior or burn severity modeling.

Comparing ladder fuel metrics across methods within CBH categories

When methods to estimate ladder fuels metrics were compared while taking overall forest canopy structure into account, particularly the distance from the ground to the main live canopy measured by field-based CBH, clearer patterns emerged in correlations in ladder fuel metrics among methods (Figure 4). These results stress the importance of forest canopy structure to determine ladder fuels and suggest that methods for ladder fuel estimation should include canopy structure to account for differences in measurement techniques. However, by separating our analyses by CBH, we partitioned the variance among measurement methods in a way that strengthened correlations. We chose CBH as a grouping variable because of its physically meaningful relationship to ladder fuels; it defines the lower height in the forest at which a wildfire can spread into the canopy. Other studies estimating ladder fuels using multiple approaches did not consider canopy structure (e.g. George and Alonso, 2008). Perhaps, the forests in which these measurements were taken were less complex than oak woodlands and mixed-conifer forests, with a wide range of forest structure (George and Alonso, 2008). In particular, oak woodlands have a dense understory of annual or perennial shrubs and resprouts, causing their community structure to be much more complex than other ecosystem types (George and Alonso, 2008; Jimerson and Carothers, 2002). As such, we recommend that future research explore the complex interactions between forest structure (e.g., CBH, stem density, canopy cover, etc.) and other site-level variables (e.g., frequency and severity of past disturbance, solar radiation) in these heterogeneous ecosystems, as their interactions are necessary to predict ladder fuels, yet the specific ecological mechanisms are still unknown.

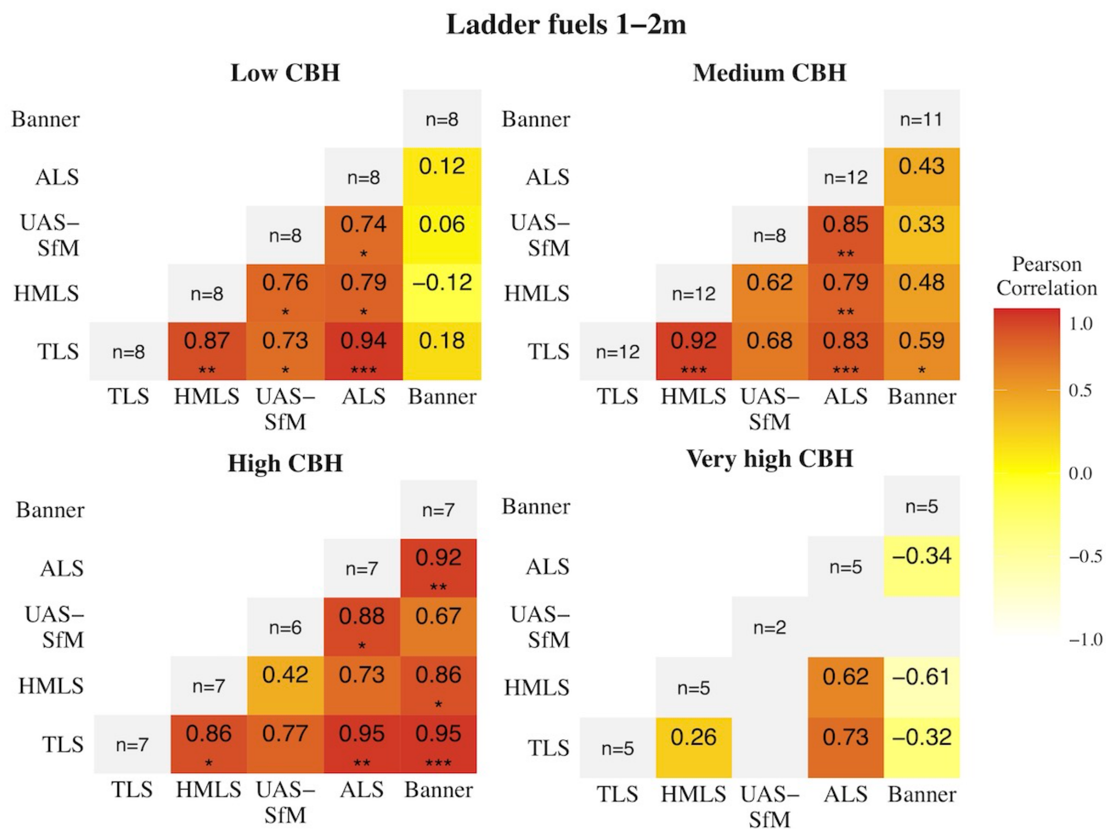


Figure 4: Heatmap of Pearson correlation coefficients to compare only the ladder fuel metric at 1-2 m by CBH category across all methods. Significance is as follows: *** p-value ≤ 0.001, ** 0.001 > p-value ≤ 0.01, * 0.01 > p-value ≤ 0.05. Note the removal of UAS-SfM from the very high CBH due to low sample size (n=2).

Comparing common ladder fuel metrics across methods

While we defined ladder fuel strata in 1-m increments, we were also interested in comparing a ladder fuel metric from 1-4 m (Green et al. 2020) across methods and the ability of the ground-based method (photo banner) to validate the 1-4 m ladder fuel metric (Figure 5). This metric was found to be an important predictor of canopy damage at the regional scale (Green et al. 2020), and is produced at the state scale for fuels management and fire behavior modeling (California Forest Observatory; 2020)

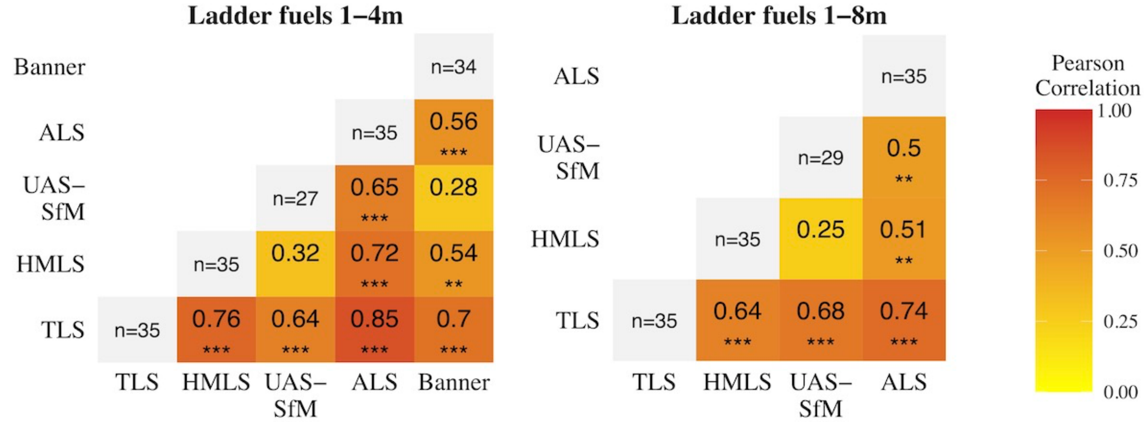


Figure 5: Heatmap of Pearson correlation coefficients to compare ladder fuel metrics 1-4 m and 1-8 m across methods. Significance is as follows: *** p-value ≤ 0.001, ** 0.001 > p-value ≤ 0.01, * 0.01 > p-value ≤ 0.05

When forest canopy structure (via CBH) was taken into consideration, the photo banner was significantly similar to the 1-4 m ladder fuel metric from TLS and ALS in high and very high CBH plots, and significantly similar to TLS, ALS, and HMLS in medium CBH plots (Figure 6). While no other studies to date have compared the photo banner to TLS or HMLS data, Kramer et al. (2016) found that the photo banner could be used to validate ALS measurements of ladder fuels. Our results indicate that remote sensing measurements of this metric can be measured using different approaches (i.e., TLS, HMLS) and then assist in the calibration and validation of spaceborne optical, LiDAR and SAR missions (e.g., GEDI, ICESAT-2, NISAR, BIOMASS) to help inform predictive models of canopy damage at varying spatial scales (Levick et al., 2021).

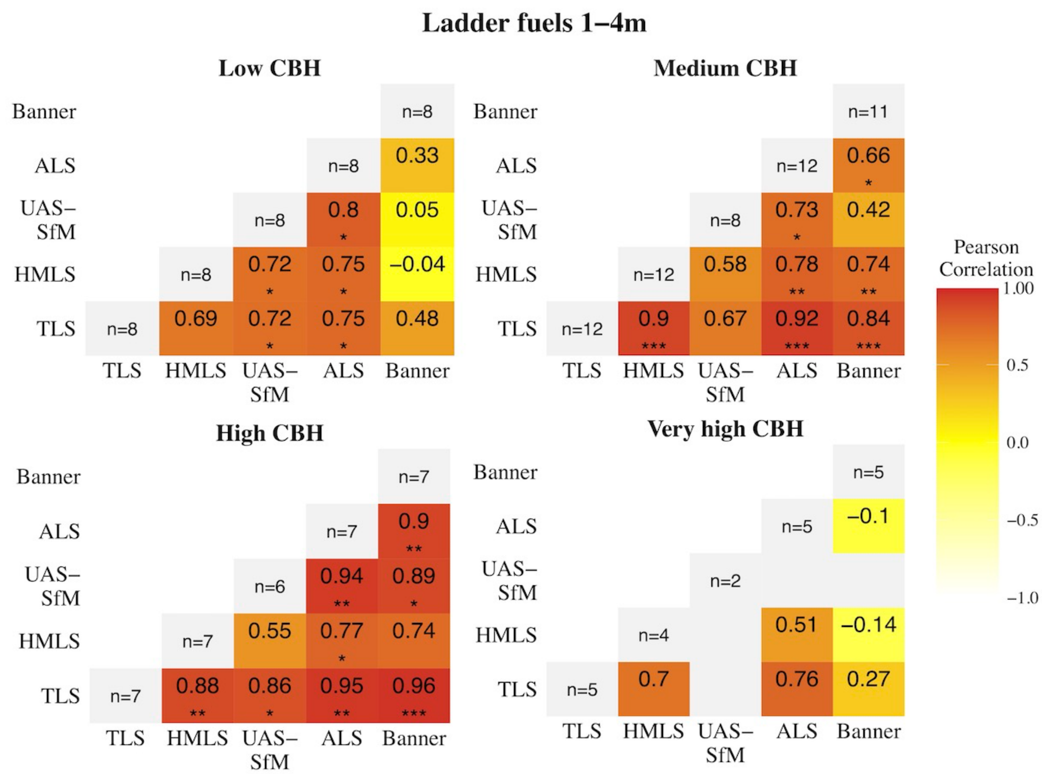


Figure 6: Heatmap of Pearson correlation coefficients for ladder fuel metric 1-4 m by CBH category across all methods. Significance is as follows: *** p-value ≤ 0.001, ** 0.001 > p-value ≤ 0.01, * 0.01 > p-value ≤ 0.05.

Similar to Hillman and colleagues (2021b), UAS-SfM methods were unable to consistently detect sub-canopy structure when compared to TLS, particularly in forests with closed canopies. We explored this technology due to its relatively low cost compared to airborne small-footprint lidar, mounted either on a plane or UAS. Despite its limitations, we found that UAS-SfM was significantly correlated with ALS across a range of strata, and correlations strengthened considerably with ALS and TLS when considering CBH classes. Interestingly, across plots differences between TLS and UAS ladder fuels were more pronounced at the upper strata (average UAS had 18% more than TLS in the 7-8 m stratum vs. only 1% higher in the 1-2 m stratum), whereas differences between UAS and ALS in these strata were more balanced (on average, about 10% more in UAS). Although the RdNBR UAS-SfM model did not perform as well as TLS or ALS, it had an R^2 from 0.50 to 0.53, slightly better than HMLS (although the UAS-SfM model had fewer total plots, as previously mentioned). We thus find that there is some value in UAS-SfM, particularly in forests with gaps in the canopy, such as oak woodlands or managed stands, where some lower-canopy and ground points are detected in the SfM process. In addition, our previous research found multispectral UAS-SfM to be useful for monitoring changes in upper-canopy structure and greenness after wildfires (Reilly et al., 2021). We also note that multi-angle views can improve detection of sub-canopy structure with UAS-SfM

(Lamping et al., 2021), a factor that we could not explore as we were constrained to a nadir view by our UAS and sensor equipment.

Modeling the relationship between ladder fuels and burn severity
When the utility of ladder fuel density metrics to predict wildfire burn severity (as predicted by RdNBR) were examined, the most common ladder fuels strata included were 1-2 m and 3-4 m. While 7-8 m was also included in the model with HMLS data, there was a low density of points in this dataset (Table 1; Table 2). When comparing methods to collect ladder fuel data and predict RdNBR, the TLS model had the highest predictive power ($R^2 = 0.67$). TLS provides very detailed data of forest structure (Disney, 2019) and thus was expected to be a useful approach for collecting data to predict RdNBR. In addition, the model using ALS data also had high predictive capability ($R^2 = 0.66$), similar to TLS but using different metrics. Green et al. (2020) also showed that ladder fuels from 1-4 m measured by ALS were a significant predictor of canopy damage, with additional topographic variables ($R^2 = 0.63$ for non-wind driven fires; $R^2 = 0.56$ for wind-driven fires).

Models using ladder fuel metrics collected from HMLS and UAS-SfM approaches were not as useful to predict RdNBR (Table 3). While Bauwens et al. (2016) found HMLS outperformed TLS when estimating forest inventory metrics, HMLS is less reliable for density metrics, as point density varies based on length of scan and the walking path taken by the user. There was a very low correlation between the two methods at high CBH for 1-2 m (r = +0.26) for the present study, highlighting the effects of differences in data acquisition and point distribution between the two methods. While data collected from UAS-SfM produced models with moderate predictive capability, this method is only useful and reliable under certain forest conditions, such as an open-canopy forest. Importantly, the strength of ladder fuel variables to predict RdNBR were stronger in all analyses when CBH was included. This finding agrees with those of Fernández-Guisuraga et al. (2021) who found that severe ecosystem damage was mainly driven by vegetation structure rather than topography or patch size, with different roles of pre-fire fuel structure parameters.

	Model	**R^2**	**SBC**	**Sample Size**			
				Total	**NC**	**Low**	**Moderate+**
TLS	Int, 1-2m*CBH, CBH	0.67	255.4	25	3	13	9
HMLS	Int, 7-8*CBH	0.44	259.0	25	3	13	9
UAS-SfM	Int, 7-8, 3-4*CBH	0.53	174.0	17	3	9	5
ALS	Int, 1-2m*CBH, 3-4, 5-6*CBH	0.66	252.7	25	3	13	9
Banner	Int	0.00	251.2	24	3	12	9

Table 3: GLM model results using RdNBR. The overall sample size for each method and the sample size broken down into burn severity categories (no change, low, moderate and above) are also shown.

Science delivery

The results of this study have been presented to 30+ scientists and land managers in the Terrestrial Biodiversity and Climate Change Collaborative through a workshop presentation and discussion in June 2021. A summary of the preliminary findings was presented at Sonoma State University's inaugural 3 Minute Thesis Competition in January 2021. A video on Lisa Bentley's website also includes results of this study. Additionally, results have been presented to the public, international scientists, and fellow SSU students and faculty during the oral presentation associated with Brieanne Forbes' M.S. thesis defense. The project findings have been presented as a poster at the American Geophysical Union (AGU) Annual Meeting in December 2021 and Sonoma State University at their Annual Research Symposium (April 2020). A management-oriented summary guide has been created to be distributed throughout the Fire Science Network and to land managers. Lastly, a manuscript of this study has been submitted to a special edition of the journal *Frontiers in Forests and Global Change* called "Recent Advances in Remote Sensing of Forest Fires" and is currently in peer review. Additional outreach is planned in the near future.

Conclusions and Implications for Management/Policy and Future Research

Our study showed that measurements of ladder fuels using various remote sensing approaches are able to moderately estimate wildfire burn severity. In the future, additional forest structure variables, such as canopy height, spatial context of surrounding vegetation types, and topography, which have been shown to be important in predicting burn severity in our ecosystem (Green et al. 2020) and climate variables, especially annual mean vapor-pressure deficit, wind speed, and burning index (Chen et al., 2021), as well as those related to weather and fire propagation could also help inform future models as they may exert dominant control over burn severity in relation to topography (Viedma et al., 2015; García-Llamas et al., 2020), particularly under extreme climatic conditions (Turner and Romme, 1994). With a more robust model that includes additional forest structure, topographic and climate variables collected over more plots, the role of ladder fuels can be further assessed and extrapolated to broader spatial scales which has significant applications to scaling fire risk, perhaps using space-based LiDAR (i.e., NASA's GEDI; Leite et al., 2022) or a state-wide forest monitoring system such as the California Forest Observatory, which estimates ladder fuels and CBH from multispectral satellite imagery calibrated with ALS.

In addition, the inclusion of a single broad forest structure metric (CBH) had a significant impact on model significance. Therefore, future studies should explore which specific aspect of forest structure (i.e., stand density, canopy cover, canopy height, and live crown ratio) would be the fundamental determinant of ladder fuel density and what other forest attributes can enhance model outcomes. Many studies have accurately estimated CBH from ALS data (Andersen et al., 2005; Chamberlain et al., 2021; Kelly et al., 2017; Luo et al., 2018; Moran et al., 2020; Stefanidou et al., 2020), and a few studies have estimated CBH with TLS data (García et al., 2011, Novotny et al., 2021), so ideally these forest structure variables could be estimated via remote sensing, to maintain a continuity in data collection.

Lastly, while we used a density-based approach to estimate ladder fuels using remote sensing data, future studies should explore the use of voxel-based metrics or standardization of density metrics using voxels (Hillman et al. 2021). While Atchley et al. (2021) and Green et al. (2020) found significant results using density methods, voxels, a unit which defines 3D space, could be an alternative way of calculating ladder fuels. Wilson et al. (2021) found voxels to effectively explain the effects of logging and wildfire on vertical fuel continuity by using these methods to explain forest structure. Remote sensing methods, which are generally advancing more rapidly than those of fire behavior modelling, present an opportunity to forge new pathways in forest fuel estimation (Gale et al., 2021).

Literature Cited

Abatzoglou, J.T., and Williams, A.P. (2016). Impact of Anthropogenic Climate Change on Wildfire across Western US Forests. *Proceedings of the National Academy of Sciences* 113:42, 11770-11775. doi: 10.1073/pnas.1607171113.

Andersen, H.-E., McGaughey, R. J., and Reutebuch, S. E. (2005). Estimating Forest Canopy Fuel Parameters using LIDAR Data. *Remote Sensing of Environment* 94, 441–449. doi:10.1016/j.rse.2004.10.013.

Bauwens, S., Bartholomeus, H., Calders, K., and Lejeune, P. (2016). Forest Inventory with Terrestrial LiDAR: A Comparison of Static and Hand-Held Mobile Laser Scanning. *Forests* 7:127. doi:10.3390/f7060127.

Brede, B., Calders, K., Lau, A., Raumonen, P., Bartholomeus, H. M., Herold, M., and Kooistra, L. (2019). Non-Destructive Tree Volume Estimation through Quantitative Structure Modelling: Comparing UAV Laser Scanning with Terrestrial LIDAR. *Remote Sensing of Environment* 233:111355. doi: 10.1016/j.rse.2019.111355.

Campbell, M. J., Dennison, P. E., Tune, J. W., Kannenberg, S. A., Kerr, K. L., Codding, B. F., et al. (2020). A Multi-Sensor, Multi-Scale Approach to Mapping Tree Mortality in Woodland Ecosystems. *Remote Sensing of Environment* 245:111853. doi:10.1016/j.rse.2020.111853.

California Forest Observatory (2020). A Statewide Tree-Level Forest Monitoring System. Salo Sciences, Inc. San Francisco, CA https://forestobservatory.com [Accessed October 24, 2021].

Chen, Y., Zhu, X., Yebra, M., Harris, S., and Tapper, N. (2016). Strata-Based Forest Fuel Classification for Wild Fire Hazard Assessment using Terrestrial LiDAR. *J. Appl. Remote Sens* 10:046025. doi:10.1117/1.JRS.10.046025.

Chudá, J., Hunčaga, M., Tuček, J., and Mokroš, M. (2020). The Handheld Mobile Laser Scanners as a Tool for Accurate Positioning Under Forest Canopy. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* XLIII-B1-2020, 211–218. doi:10.5194/isprs-archives-XLIII-B1-2020-211-2020.

Dennison, P. E., Brewer, S. C., Arnold, J. D., and Moritz, M. A. (2014). Large Wildfire Trends in the Western United States, 1984-2011. *Geophys. Res. Lett.* 41:8, 2928–2933. doi:10.1002/2014GL059576.

Disney, M. (2019). Terrestrial Li DAR : A Three-Dimensional Revolution in How We Look at Trees. *New Phytol* 222, 1736–1741. doi:10.1111/nph.15517.

Donager, J. J., Meador, A. J. S., and Blackburn, R. C. (2021). Adjudicating Perspectives on Forest Structure: How Do Airborne, Terrestrial, and Mobile Lidar-Derived Estimates Compare? *Remote Sensing* 13:2297. doi:10.3390/rs13122297.

Duff, T. J., Bell, T. L., and York, A. (2013). Predicting Continuous Variation in Forest Fuel Load using Biophysical Models: A Case Study in South-Eastern Australia. *Int. J. Wildland Fire* 22:3, 318–332. doi: 10.1071/WF11087.

Duff, T. J., Cawson, J. G., and Penman, T. D. (2019). Determining Burnability: Predicting Completion Rates and Coverage of Prescribed Burns for Fuel Management. *For. Ecol. Manage.* 433, 431–440. 10.1016/j.foreco.2018.11.009.

Fernández-Guisuraga, J. M., Suárez-Seoane, S., García-Llamas, P., and Calvo, L. (2021). Vegetation Structure Parameters Determine High Burn Severity Likelihood in Different Ecosystem Types: A Case Study in a Burned Mediterranean Landscape. *Journal of Environmental Management* 288:112462. doi:10.1016/j.jenvman.2021.112462.

Gale, M. G., Cary, G. J., Van Dijk, A. I. J. M., and Yebra, M. (2021). Forest Fire Fuel Through the Lens of Remote Sensing: Review of Approaches, Challenges and Future Directions in the Remote Sensing of Biotic Determinants of Fire Behaviour. *Remote Sensing of Environment* 255:112282. doi:10.1016/j.rse.2020.112282.

García, M., Danson, F. M., Riaño, D., Chuvieco, E., Ramirez, F. A., and Bandugula, V. (2011). Terrestrial Laser Scanning to Estimate Plot-Level Forest Canopy Fuel Properties. *International*

Journal of Applied Earth Observation and Geoinformation 13, 636–645. doi:10.1016/j.jag.2011.03.006.

George, M. R., and Alonso, M. F. (2008). Oak Woodland Vegetation Dynamics: A State and Transition Approach. opportunities. [Technical Report]. *PSW-GTR-217. Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station* 12.

González-Ferreiro, E., Arellano-Pérez, S., Castedo-Dorado, F., Hevia, A., Vega, J. A., Vega-Nieva, D., et al. (2017). Modelling the Vertical Distribution of Canopy Fuel Load using National Forest Inventory and Low-Density Airbone Laser Scanning Data. *PLoS ONE* 12: e0176114. doi:10.1371/journal.pone.0176114.

Green, K., Tukman, M., Loudon, D., Gaffney, K., and Clark, M. (2020). Sonoma County Complex Fires of 2017: Remote Sensing Data and Modeling to Support Ecosystem and Community Resiliency. *California Fish and Wildlife, Fire Special Issue,* 14-45.

Gupta, V., Reinke, K., Jones, S., Wallace, L., and Holden, L. (2015). Assessing Metrics for Estimating Fire Induced Change in the Forest Understorey Structure Using Terrestrial Laser Scanning. *Remote Sensing* 7, 8180–8201. doi:10.3390/rs70608180.

Hillman, S., Hally, B., Wallace, L., Turner, D., Lucieer, A., Reinke, K., et al. (2021a). High-Resolution Estimates of Fire Severity—An Evaluation of UAS Image and LiDAR Mapping Approaches on a Sedgeland Forest Boundary in Tasmania, Australia. *Fire* 4, 14. doi:10.3390/fire4010014.

Hillman, S., Wallace, L., Lucieer, A., Reinke, K., Turner, D., and Jones, S. (2021b). A comparison of terrestrial and UAS sensors for measuring fuel hazard in a dry sclerophyll forest. *International Journal of Applied Earth Observation and Geoinformation* 95, 102261. doi:10.1016/j.jag.2020.102261.

Hyyppä, E., Yu, X., Kaartinen, H., Hakala, T., Kukko, A., Vastaranta, M., et al. (2020). Comparison of Backpack, Handheld, Under-Canopy UAV, and Above-Canopy UAV Laser Scanning for Field Reference Data Collection in Boreal Forests. *Remote Sensing* 12:3327. doi:10.3390/rs12203327.

Jain, P., Wang, X., and Flannigan, M. D. (2017). Trend Analysis of Fire Season Length and Extreme Fire Weather in North America between 1979 and 2015. *International Journal of Wildland Fire* 26:12, 1009-1020. doi: 10.1071/WF17008.

Jakubowski, M. K., Guo, Q., and Kelly, M. (2013). Tradeoffs between lidar pulse density and forest measurement accuracy. *Remote Sensing of Environment* 130, 245–253. doi:10.1016/j.rse.2012.11.024.

Jimerson, T. M., and Carothers, S. K. (2002). Northwest California Oak Woodlands: Environment, Species Composition, and Ecological Status. [Technical Report]. *PSW-GTR-184, Albany, CA: U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station* 13.

Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., et al. (2015). Climate-Induced Variations in Global Wildfire Danger from 1979 to 2013. *Nature communications* 6:1, 1-11. doi: 10.1038/ncomms8537.

Joyce, K.E.; Anderson, K.; Bartolo, R.E. Of Course We Fly Unmanned—We're Women!. *Drones* (2021). 5, 21. doi: 10.3390/drones5010021.

Kelly, M., and Di Tommaso, S. (2015). Mapping Forests with Lidar Provides Flexible, Accurate Data with Many Uses. *Cal Ag* 69, 14–20. doi:10.3733/ca.v069n01p14.

Kramer, H., Collins, B., Kelly, M., and Stephens, S. (2014). Quantifying Ladder Fuels: A New Approach Using LiDAR. *Forests* 5, 1432–1453. doi:10.3390/f5061432.

Kelly, M., Su, Y., Di Tommaso, S., Fry, D., Collins, B., Stephens, S., et al. (2017). Impact of Error in Lidar-Derived Canopy Height and Canopy Base Height on Modeled Wildfire Behavior in the Sierra Nevada, California, USA. *Remote Sensing* 10:10. doi:10.3390/rs10010010.

Kramer, H., Collins, B., Lake, F., Jakubowski, M., Stephens, S., and Kelly, M. (2016). Estimating Ladder Fuels: A New Approach Combining Field Photography with LiDAR. *Remote Sensing* 8:766. doi:10.3390/rs8090766.

Lamping, J. E., Zald, H. S. J., Madurapperuma, B. D., and Graham, J. (2021). Comparison of Low-Cost Commercial Unpiloted Digital Aerial Photogrammetry to Airborne Laser Scanning across Multiple Forest Types in California, USA. *Remote Sensing* 13:4292. doi:10.3390/rs13214292.

Levick, S. R., Whiteside, T., Loewensteiner, D. A., Rudge, M., and Bartolo, R. (2021). Leveraging TLS as a Calibration and Validation Tool for MLS and ULS Mapping of Savanna Structure and Biomass at Landscape-Scales. *Remote Sensing* 13:257. doi:10.3390/rs13020257.

Marselis, S. M., Yebra, M., Jovanovic, T., and van Dijk, A. I. J. M. (2016). Deriving Comprehensive Forest structure Information from Mobile Laser Scanning Observations Using Automated Point Cloud Classification. *Environmental Modelling and Software* 82, 142-151. doi:10.1016/j.envsoft.2016.04.025.

Menning, K. M., and Stephens, S. L. (2007). Fire Climbing in the Forest: A Semiqualitative, Semiquantitative Approach to Assessing Ladder Fuel Hazards. *Western Journal of Applied Forestry* 22, 88–93. doi:10.1093/wjaf/22.2.88.

Miller, J. D., and Thode, A. E. (2007). Quantifying Burn Severity in a Heterogeneous Landscape with a Relative Version of the Delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment* 109, 66–80. doi:10.1016/j.rse.2006.12.006.

Ottmar, R. D., Sandberg, D.V., Riccardi, C. L., and Prichard, S. J. (2007). An Overview of The Fuel Characteristic Classification System—Quantifying, Classifying, and Creating Fuelbeds for Resource Planning. *Can. J. For. Res.* 37:12, 2383–2393. doi:10.1 139/X07-077

Reilly, S., Clark, M. L., Bentley, L. P., Matley, C., Piazza, E., and Oliveras Menor, I. (2021). The Potential of Multispectral Imagery and 3D Point Clouds from Unoccupied Aerial Systems (UAS) for Monitoring Forest Structure and the Impacts of Wildfire in Mediterranean-Climate Forests. *Remote Sensing* 13, 3810. doi:10.3390/rs13193810.

Rowell, E., Loudermilk, E. L., Hawley, C., Pokswinski, S., Seielstad, C., Queen, Ll., et al. (2020). Coupling Terrestrial Laser Scanning with 3D Fuel Biomass Sampling for Advancing Wildland Fuels Characterization. *Forest Ecology and Management* 462:117945. doi:10.1016/j.foreco.2020.117945.

Skowronski, N., Clark, K., Nelson, R., Hom, J., and Patterson, M. (2007). Remotely Sensed Measurements of Forest Structure and Fuel Loads in the Pinelands of New Jersey. *Remote Sensing of Environment* 108, 123–129. doi:10.1016/j.rse.2006.09.032.

Stephens, S. L., McIver, J. D., Boerner, R. E.J., Fettig, C. J., Fontaine, J. B., Hartsough, B. R., et al. (2012). The Effects of Forest Fuel-Reduction Treatments in The United States. *Bioscience* 62:6, 549–560. doi:10.1525/bio.2012.62.6.6.

Watershed Sciences. (2016). Sonoma County Vegetation Mapping and Lidar Program. [Technical Report]. *Watershed Sciences, Inc. Applied Remote Sensing and Analysis* https://sonomaopenspace.egnyte.com/dl/8DukhuIXgT/ [Accessed June 20, 2021].

Wilkes, P., Lau, A., Disney, M., Calders, K., Burt, A., Gonzalez de Tanago, J., et al. (2017). Data Acquisition Considerations for Terrestrial Laser Scanning of Forest Plots. *Remote Sensing of Environment* 196, 140–153. doi:10.1016/j.rse.2017.04.030.

Appendix A: Contact Information for Key Project Personnel

Lisa Patrick Bentley

lisa.bentley@sonoma.edu

Brieanne Forbes

brieanne.k.forbes@gmail.com

Appendix B: List of Completed/Planned Scientific/Technical Publications/Science Delivery Products

- Terrestrial Biodiversity and Climate Change Collaborative presentation.
- Sonoma State 3 Minute Thesis Competition presentation.
- The 3D Forests Project video on Lisa Bentley's website: https://lisapatrickbentley.org/?page_id=126
- M.S. thesis defense presentation
- M.S. thesis
- American Geophysical Union (AGU) poster
- Sonoma State University Annual Research Symposium poster.
- Management-oriented summary guide
- Manuscript
- Additional outreach is planned in the near future.

Appendix C: Metadata

As required by the JFSP policy, a copy of our metadata document(s) will be uploaded to the JFSP online database as part of the final report submission. The following is a citation of the data in the FS Research Data Archive:

Forbes, Brieanne K.; Reilly, Sean P.; Clark, Matthew L.; Ferrell, Ryan M.; Kelly, Allison C.; Krause, Paris D.; Matley, Corbin D.; O'Neil, Michael W.; Villasenor, Michelle T.; Disney, Mathias I.; Wilkes, Phil; Bentley, Lisa P. 2021. Plot-level ladder fuel estimation from a suite of remote sensing and field methods. Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2021-0101

Here you can find a Comma-separated values (CSV) file containing ladder fuel estimation data, canopy base height, and Relativized delta Normalized Burn Ratio. Additionally, it includes a CSV file containing easting and northing coordinates of measurement plot centers, and a Joint Photographic Experts Group