Estimating Surface Fuel Density from TLS and ALS: A Two-Tiered Approach that Accounts for Sampling Scale

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1. Introduction

Terrestrial Laser Scanning (TLS) and Airborne Laser Scanning (ALS) collect 3D point cloud data that have been related to destructive harvest plot measures of surface fuel densities using regression models (Hudak et al. 2016, Rowell et al. 2020). Higher resolution makes TLS data well suited for characterizing surface fuel components at plot scale, whereas synoptic coverage makes ALS data well suited for surface fuel density mapping at landscape scale. We tested a two-tiered modelling approach, where surface fuel density was estimated with TLS metrics in large plots; these estimates were in turn used to train a second model to map fuel density from ALS metrics across an ~1000 ha area in the 102,716 ha Blackwater River State Forest (BRSF) in the Florida panhandle, USA. There, 362 ha was burned on 30 August 2019, in coordination with the NOAA/NASA Fire Influence on Regional to Global Environments and Air Quality (FIREX-AQ) campaign to measure smoke emissions from a DC-8 aircraft that flew multiple transects through the smoke plume. Our larger goal for this paper and in support of FIREX-AQ was to accurately characterize fuels on the ground, to help constrain the two largest sources of uncertainty in emissions estimates: fuel load and fuel consumption. This analysis focused on fuel load.

2. Methods

TLS data was collected across six large plots ranging in size from 39-351.5 m² that were comprised primarily of three surface fuel components: shrubs, wiregrass, and litter. Bulk densities of these components were measured in 3D destructive harvest plots, following the methods of Hawley et al. (2018). These component fuel density estimates were used as the response variables to predict fuel densities from height, surface area, volume, and porosity metrics derived from TLS, following Rowell et al. (2020). In turn, these TLS estimates were used as the response variables to predict component fuel densities from ALS-derived canopy height and density metrics, per Hudak et al. (2016). The predictive ALS models were subsequently applied to the same selected ALS metrics to generate surface fuel density maps of each fuel component. The mapped surface fuel estimates were subsequently adjusted upwards in proportion to overstory canopy cover to correct for overstory occlusion of the ALS signal (Hudak et al. 2016). Multiple linear regression was used for all models, and only two variables were selected per model due to the small sample size of only six plots. Total fuel densities were calculated as the sum of the shrub, grass, and litter fuel density estimates at all three levels (i.e., field measures, TLS estimates).

3. Results and Discussion

TLS and ALS metrics selected as predictors in the models are shown in Table 1. Although not all predictors were significant, the models predicting shrub, grass, and litter fuel densities were all

significant, for both TLS (Figure 1) and ALS (Figure 2). Based on the relatively low RMSE for the models at each step, the two-tiered approach appears to have worked well for mapping densities of surface fuel components at the BRSF burn, despite having only six sample plots. We believe that the large size of the six training plots was highly conducive to both TLS and ALS characterization, as evidenced by the high Adj. R² statistics (Figure 2).

Table 1. Linear regression models predicting shrub, grass, and litter fuel density (g/m^3) from A) TLS and B) ALS metrics. Models were limited to two predictors given that there were only six field plots.

Sensor	Fuel	cs. Models were lim Selected Metric	^	Estimate	Std. Error	t value	Pr(> t)	Significan
	Component							
A) TLS								
	Shrub							
		(Intercept)		20.8800	6.7640	3.087	0.00314	**
		Surface area sum		1.04E-05	3.02E-06	3.456	0.00105	**
		Porosity mean		-21.0300	6.8290	-3.079	0.00321	**
	Grass							
		(Intercept)		-5.9570	5.0890	-1.171	0.2523	
		Surface area sum		5.73E-06	1.22E-05	0.472	0.6411	
		Vertical plant area densit	Ý	0.3183	0.1170	2.72	0.0115	*
	Litter							
		(Intercept)		11.7570	57.7820	0.203	0.842	
		Porosity standard deviation	on	365.0640	205.9290	1.773	0.102	
		Horizontal plant area den	sity	2.9720	2.1390	1.389	0.19	
) ALS								
	Shrub							
		(Intercept)		127.2032	21.7838	5.839	0.01001	*
		Understory height 90 th pe	rcentile	-164.5434	27.7899	-5.921	0.00962	**
		Understory density, 0-15	cm	1.5737	0.5817	2.705	0.07344	
	Grass							
		(Intercept)		200.1723	6.1741	32.421	6.45E-05	***
		Understory density, 15-50) cm	-5.7682	0.3455	-16.695	0.000468	***
		Canopy skewness		-10.4343	1.1893	-8.773	0.003119	**
	Litter							
		(Intercept)		440.0075	47 2404	25 424	0.000133	***
		(intercept)		440.8075	17.3401	25.421	0.000122	
		Understory density, 15-50) cm	440.8075 -7.8391	17.3401 1.1797	-6.645	0.000133	**
) cm					**
		Understory density, 15-50) cm	-7.8391	1.1797	-6.645	0.006945	**
		Understory density, 15-50) cm	-7.8391	1.1797	-6.645	0.006945	**
s	Shrub Bulk Density	Understory density, 15-50) cm	-7.8391	1.1797 0.9672	-6.645	0.006945	**
S 0.03	shrub Bulk Density	Understory density, 15-50) cm	-7.8391 -1.9054	1.1797 0.9672	-6.645	0.006945	**
		Understory density, 15-50) cm	-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645	0.006945	**
0.03		Understory density, 15-50		-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645	0.006945	**
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0.03		Understory density, 15-50 Canopy density, 0-15 cm		-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645	0.006945	
0.03		Understory density, 15-50 Canopy density, 0-15 cm		-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645	0.006945	Strata (cm)
0.03		Understory density, 15-50 Canopy density, 0-15 cm		-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645	0.006945	
0.03		Understory density, 15-50 Canopy density, 0-15 cm		-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645 -1.97	0.006945	Strata (cm)
		Understory density, 15-50 Canopy density, 0-15 cm		-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444	Strata (cm)
0.03		Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) © 0.25 © 0.35 © 0.35 + 0.45 + 0.45 • 0.85 • 0.85	-7.8391 -1.9054 Grass Bulk Der	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444	Strata (cm)
Predicted Dry Weight(g m ³) Provided Dry Weight(g m ³)		Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) □ 0.25 0.035 0.045 + 0.65 • 0.85 • 0.85 1	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444 MSE = 9.14 Jj. R2 = 0.41 value < 0.001	Strata (cm)
Predicted Dry Weight(g m ³) Provided Dry Weight(g m ³)		Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) © 0.25 © 0.35 © 0.35 + 0.45 + 0.45 • 0.85 • 0.85	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444	Strata (cm)
Predicted Dry Weight(g m ³)		Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) □ 0.25 0.035 0.045 + 0.65 • 0.85 • 0.85 1	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444 MSE = 9.14 Jj. R2 = 0.41 value < 0.001	Strata (cm)
Predicted Dry Weight(g m ³)	a)	Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) □ 0.25 0.035 0.045 + 0.65 • 0.85 • 0.85 1	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444 MSE = 9.14 Jj. R2 = 0.41 value < 0.001	Strata (cm)
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0.03 Litter 0.00 Litter 0.00	a)	Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) 0.25 0.354 + 0.65 0.055 0.055 0.055 0.055 0.055	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444 MSE = 9.14 Jj. R2 = 0.41 value < 0.001	Strata (cm)
0.03 Litter 0.00 Litter 0.00	a)	Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) 0.25 0.354 + 0.65 0.055 0.055 0.055 0.055 0.055	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444 MSE = 9.14 Jj. R2 = 0.41 value < 0.001	Strata (cm)
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0.03 Litter 0.00 0.02 0.00 0.01 0.00 0.01	a)	Understory density, 15-50 Canopy density, 0-15 cm	Strata (cm) 0.25 0.354 + 0.65 0.055 0.055 0.055 0.055 0.055	-7.8391 -1.9054	1.1797 0.9672	-6.645 -1.97	0.006945 0.143444 MSE = 9.14 Jj. R2 = 0.41 value < 0.001	Strata (cm)

Figure 1: Linear regression models predicting destructive harvest plot measurements of a) shrub, b) grass, and c) litter fuel density (g/m3) from two TLS metrics (Table 1a), and d) total surface fuel density, calculated as the sum of the shrub, grass, and litter components. Plot symbols in a) and b) legends indicate the midpoints of 10 cm interval height strata above the ground.

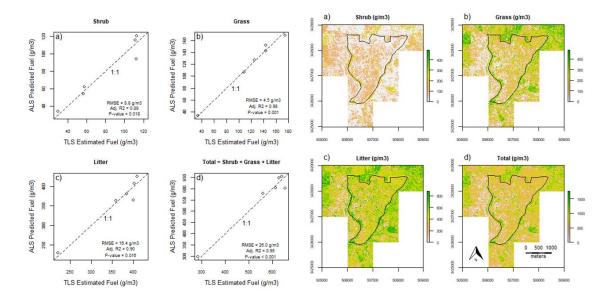


Figure 2: At left are linear regression models (left) predicting TLS estimates of a) shrub, b) grass, and c) litter fuel density (g/m3) from two ALS metrics (Table 1b), and d) total surface fuel density, calculated as the sum of the shrub, grass, and litter components. At right are the corresponding maps, with the planned burn perimeter overlaid in black.

4. Conclusion and Ongoing Work

These ALS-derived surface fuel density maps, trained with TLS data that serves to bridge the scaling gap between ALS and locally collected destructive harvest plot datasets, provide more refined estimates of surface fuel component densities than can be estimated by any other current method. We are currently validating these maps with independent estimates of fuel loads and consumption collected pre- and post-fire at 25 paired sample plots within the burn area. These data will be used to assess biases and constrain the uncertainties in estimating smoke emissions measured with instruments on board the DC-8. Lessons learned at this BRSF burn, which was well characterized from both a fuels and emissions standpoint, will help guide analyses on other FIREX-AQ fires sampled in 2019.

Acknowledgements

Funding was provided by NASA FIRECHEM Award 80NSSC18K0685, JFSP FASMEE Award 15-S-01-01, and DOD SERDP Award RC19-1064.

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