

Coarse woody debris: Pre- and post-Tubbs fire

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Overview

The aim of this research was to understand the impact of the 2017 Tubbs fire on fuel loads. Our objective was to evaluate the impact of prescribed fire on fuel loads over time for five coarse woody debris fuel classes: 1-hr, 10-hr, 100-hr, 1000-hr rotten, and 1000-hr sound. To meet this objective, we compared the pre- and post-fire levels of these five lag-time fuel classes at nine long-term vegetation monitoring plots. Surveys were conducted at four time points: 2016 (1y pre-fire), 2017 (0y post-fire), 2019 (2y post-fire), and 2021 (4y post-fire). We conducted surveys along two transects per plot; each transect had one quadrat. Each time point had 18 data points: 9 plots x 2 transects x 1 quadrat.

Using the coarse woody debris data set as input, we asked the following questions:

1. Did the total fuel load (all fuel classes combined) differ between years?
2. Did fuel load differ between years by fuel class? If so, which years were different?

Fuel measurements for coarse woody debris mass We answered these questions using a time series of plot-level data for (1) the total amount of coarse woody debris and (2) the mean amount of each of the five fuel classes. We defined “total (or all) coarse woody debris” as the combined total of the the five fuel classes within a plot: 1-hr, 10-hr, 100-hr, 1000-hr rotten, 1000-hr sound.

We calculated the *plot-level mean for each fuel class* to account for replicate surveys within each plot. To calculate the *plot-level total* at each time point, we summed the plot means for all fuel classes by fuel type.

Below is a table that shows the plot-level mean at each time point for coarse woody debris (total and mean by fuel class).

fuel_class	plot_id	2016	2017	2019	2021	metric	units
All	RxF01	13.410	114.207	111.788	21.150	total	MT/ha
All	RxF02	16.327	1.684	2.693	1.475	total	MT/ha
All	RxF03	11.540	14.906	15.052	38.496	total	MT/ha
All	RxF04	39.361	0.824	7.817	16.135	total	MT/ha
All	RxF05	10.690	0.094	0.336	10.725	total	MT/ha
All	RxF06	47.333	8.666	12.473	4.054	total	MT/ha
All	RxF07	44.831	56.827	33.710	49.655	total	MT/ha
All	RxF08	18.282	64.982	35.324	4.599	total	MT/ha
All	RxF09	15.773	0.060	0.209	4.048	total	MT/ha
1-hr	RxF01	1.091	0.284	0.716	0.165	mean	MT/ha
1-hr	RxF02	0.777	0.333	0.333	0.161	mean	MT/ha
1-hr	RxF03	0.605	0.133	0.310	0.015	mean	MT/ha
1-hr	RxF04	0.531	0.162	0.472	0.325	mean	MT/ha
1-hr	RxF05	0.525	0.094	0.336	0.332	mean	MT/ha
1-hr	RxF06	0.488	0.074	0.296	0.148	mean	MT/ha
1-hr	RxF07	0.415	0.458	0.591	0.147	mean	MT/ha
1-hr	RxF08	1.198	0.031	0.079	0.046	mean	MT/ha
1-hr	RxF09	1.024	0.060	0.209	0.136	mean	MT/ha
10-hr	RxF01	7.356	1.340	0.672	1.343	mean	MT/ha
10-hr	RxF02	6.692	1.351	2.361	1.314	mean	MT/ha
10-hr	RxF03	2.963	0.985	2.635	1.665	mean	MT/ha
10-hr	RxF04	3.305	0.661	1.321	0.992	mean	MT/ha
10-hr	RxF05	6.388	0.000	0.000	2.826	mean	MT/ha
10-hr	RxF06	7.286	0.000	2.314	0.000	mean	MT/ha
10-hr	RxF07	5.956	0.000	1.646	0.328	mean	MT/ha
10-hr	RxF08	6.195	0.000	0.000	0.659	mean	MT/ha
10-hr	RxF09	9.769	0.000	0.000	1.703	mean	MT/ha
100-hr	RxF01	4.963	0.000	0.000	0.000	mean	MT/ha
100-hr	RxF02	0.000	0.000	0.000	0.000	mean	MT/ha
100-hr	RxF03	0.000	1.649	1.649	0.000	mean	MT/ha
100-hr	RxF04	6.549	0.000	1.638	1.636	mean	MT/ha
100-hr	RxF05	1.743	0.000	0.000	1.743	mean	MT/ha
100-hr	RxF06	8.199	0.000	0.000	0.000	mean	MT/ha
100-hr	RxF07	9.882	0.000	1.625	0.000	mean	MT/ha
100-hr	RxF08	10.888	1.851	0.000	0.000	mean	MT/ha
100-hr	RxF09	4.980	0.000	0.000	0.000	mean	MT/ha
1000-hr	RxF01	0.000	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF02	0.000	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF03	1.836	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF04	28.976	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF05	0.000	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF06	6.275	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF07	4.314	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF08	0.000	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF09	0.000	0.000	0.000	0.000	mean	MT/ha
rotten							
1000-hr	RxF01	0.000	112.583	110.401	19.642	mean	MT/ha
sound							
1000-hr	RxF02	8.858	0.000 ₂	0.000	0.000	mean	MT/ha
sound							
1000-hr	RxF03	6.136	12.140	10.458	36.817	mean	MT/ha
sound							
1000-hr	RxF04	0.000	0.000	4.386	13.182	mean	MT/ha

Statistical methods Statistically significant differences were identified using repeated measures analysis of variance (ANOVA) and post hoc comparisons. P-values were adjusted using the Bonferroni multiple testing correction method.

The repeated-measures ANOVA is used for analyzing data where same subjects are measured more than once. This test is also referred to as a within-subjects ANOVA or ANOVA with repeated measures. The “within-subjects” term means that the same individuals (here, individuals are plots) are measured on the same outcome variable under different time points. The main goal of a repeated measures ANOVA is to evaluate if there is a statistically significant interaction effect between within-subjects factors in explaining a continuous outcome variable. The repeated measures ANOVA makes the following assumptions about the data:

- No significant outliers in any cell of the design
- Normality: the outcome (or dependent) variable should be approximately normally distributed in each cell of the design
- Assumption of sphericity: the variance of the differences between groups should be equal

We assessed outliers using the the interquartile range (IQR; $IQR = Q3 - Q1$). Values above $Q3 + 1.5 \times IQR$ or below $Q1 - 1.5 \times IQR$ are considered as outliers. Values above $Q3 + 3 \times IQR$ or below $Q1 - 3 \times IQR$ are considered as extreme points (or extreme outliers). $Q1$ and $Q3$ are the first and third quartile, respectively. Extreme outliers can be due to data entry errors, measurement errors, or unusual values. The outlier may be included if one believes the result will not be substantially affected; this can be evaluated by comparing the result of the ANOVA with and without the outlier.

We assessed normality by visual inspection of a QQ plot for each time point. A QQ plot draws the correlation between a given data and the normal distribution. We also conducted the Shapiro-Wilk test for each time point. Using this method, normally distributed data will have p-value > 0.05 .

The assumption of sphericity was checked during the computation of the ANOVA test using the R function `anova_test()` [rstatix package]. The Mauchly’s test was internally used to assess the sphericity assumption, and the Greenhouse-Geisser sphericity correction was automatically applied to factors violating the sphericity assumption.

Check assumptions

Check for outliers No extreme outliers were found for the total fuels subset.

There were nine extreme outliers in the mean by fuel class data set. Most outliers ($n = 6$) were from the year 2021. The 1-hr and 100-hr classes each had 4 outliers. We found the following extreme outliers by fuel class:

1-hour

- 2021 (RxF03, RxF04, RxF05, RxF08)

100-hour

- 2017 (RxF03, RxF08)
- 2021 (RxF04, RxF05)

1000-hr rotten

- excluded here because too many values are close to zero

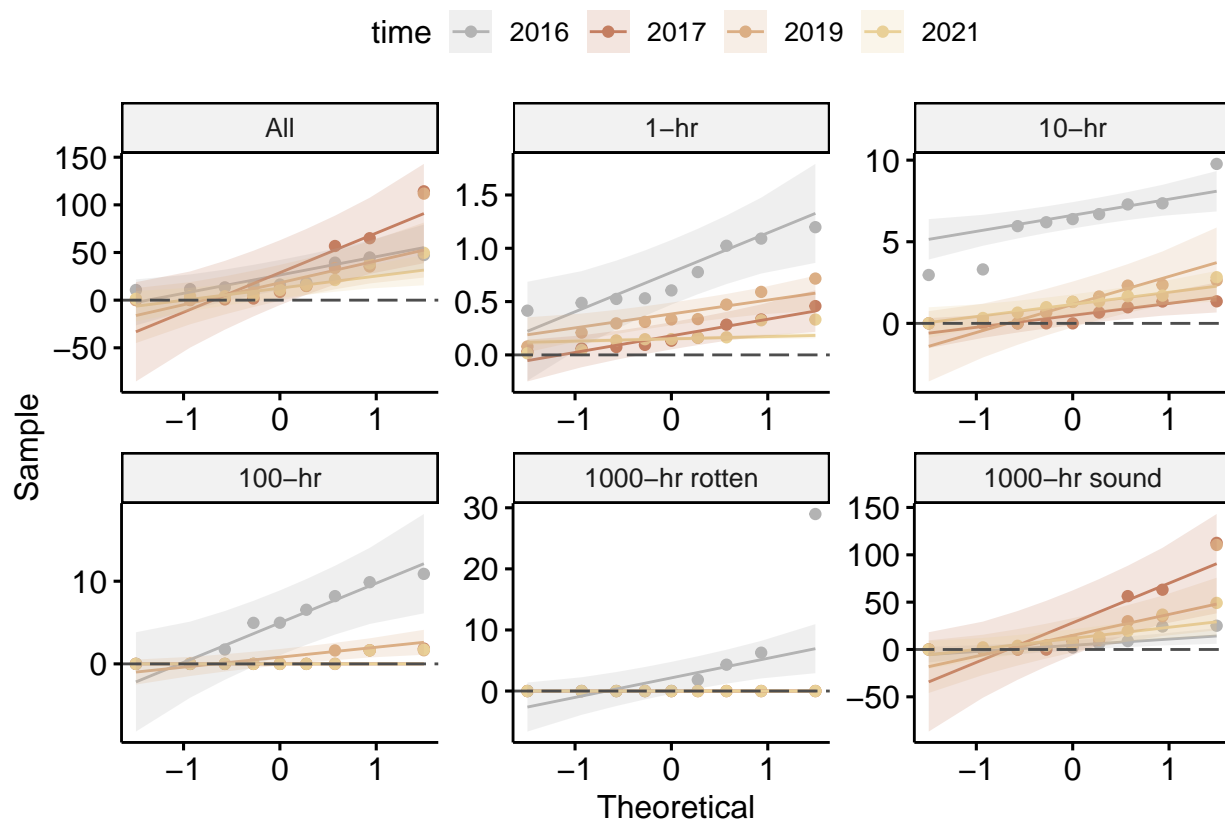
1000-hr sound

- 2016 (RxF04)

fuel_class	time	plot_id	si_value	is_outlier	is_extreme
hr0001	2021	RxF03	0.015	TRUE	TRUE
hr0001	2021	RxF04	0.325	TRUE	TRUE
hr0001	2021	RxF05	0.332	TRUE	TRUE
hr0001	2021	RxF08	0.046	TRUE	TRUE
hr0100	2017	RxF03	1.649	TRUE	TRUE
hr0100	2017	RxF08	1.851	TRUE	TRUE
hr0100	2021	RxF04	1.636	TRUE	TRUE
hr0100	2021	RxF05	1.743	TRUE	TRUE
hr1000r	2016	RxF04	28.976	TRUE	TRUE

Several points in the QQ plot fell outside the reference range.

Overall, the distribution of values by fuel class in the QQ plot didn't look terrible. As expected, the values for 1000-hr sound strayed from the reference line; this was consistent with a distribution that violated the assumptions of the Shapiro test.



Check for normality Plot-level values for total fuels were not normally distributed for three of the four time points (2016, 2017, 2019), as assessed by Shapiro-Wilk's test.

The data for the 1000-hr rotten fuel class were excluded from the normality test; an abundance of zeros in this subset caused the Shapiro test to fail. However, the data for the 1000-hr rotten fuel class are shown in a QQ plot below.

Half of the fuel class year combinations were not normally distributed, as assessed by Shapiro-Wilk's test ($n = 8$ of 16 combinations; hr1000r is excluded). Four combinations included the 1000-hr sound fuel class; three included year 2017.

Distribution not normal for: all 2016 all 2017 all 2019

hr0010 2017

hr0100 2017 hr0100 2019 hr0100 2021

hr1000s 2016 hr1000s 2017 hr1000s 2019 hr1000s 2021

fuel_class	time	is_normal	p	statistic
all	2016	FALSE	0.0133212	0.784
all	2017	FALSE	0.0090485	0.769
all	2019	FALSE	0.0016024	0.705
hr0010	2017	FALSE	0.0059536	0.754
hr0100	2017	FALSE	0.0000258	0.552
hr0100	2019	FALSE	0.0001660	0.620
hr0100	2021	FALSE	0.0000216	0.545
hr1000s	2016	FALSE	0.0036194	0.735
hr1000s	2017	FALSE	0.0066144	0.757
hr1000s	2019	FALSE	0.0008516	0.681
hr1000s	2021	FALSE	0.0319714	0.817

Identify the most appropriate transformation We applied a series of transformations to each subset, then evaluated the resulting data for outliers and normality. To create the transformed subsets, we used `scale()` from base R and four normalization functions from the `bestNormalize` package: `arcsinh_x`, `log_x`, `orderNorm`, and `sqrt_x`.

All but one of the nine outliers detected in the untransformed data were absent after the transformation was applied (by fuel class). Only one outlier was improved by any transformation: 1-hr in 2021 at Rx F08, ok with `ordnorm`.

fuel_class	time	plot_id	norm	ordnorm	si_value	sqrt	std	us_value
hr0001	2021	RxF08	FALSE	FALSE	NA	NA	NA	NA
hr0100	2016	RxF02	FALSE	FALSE	NA	NA	NA	NA
hr0100	2016	RxF03	FALSE	FALSE	NA	NA	NA	NA
hr1000r	2016	RxF04	FALSE	NA	NA	FALSE	NA	NA
hr1000s	2016	RxF06	NA	NA	FALSE	NA	FALSE	FALSE
hr1000s	2016	RxF07	NA	NA	FALSE	NA	FALSE	FALSE
hr1000s	2021	RxF07	NA	NA	FALSE	NA	FALSE	FALSE

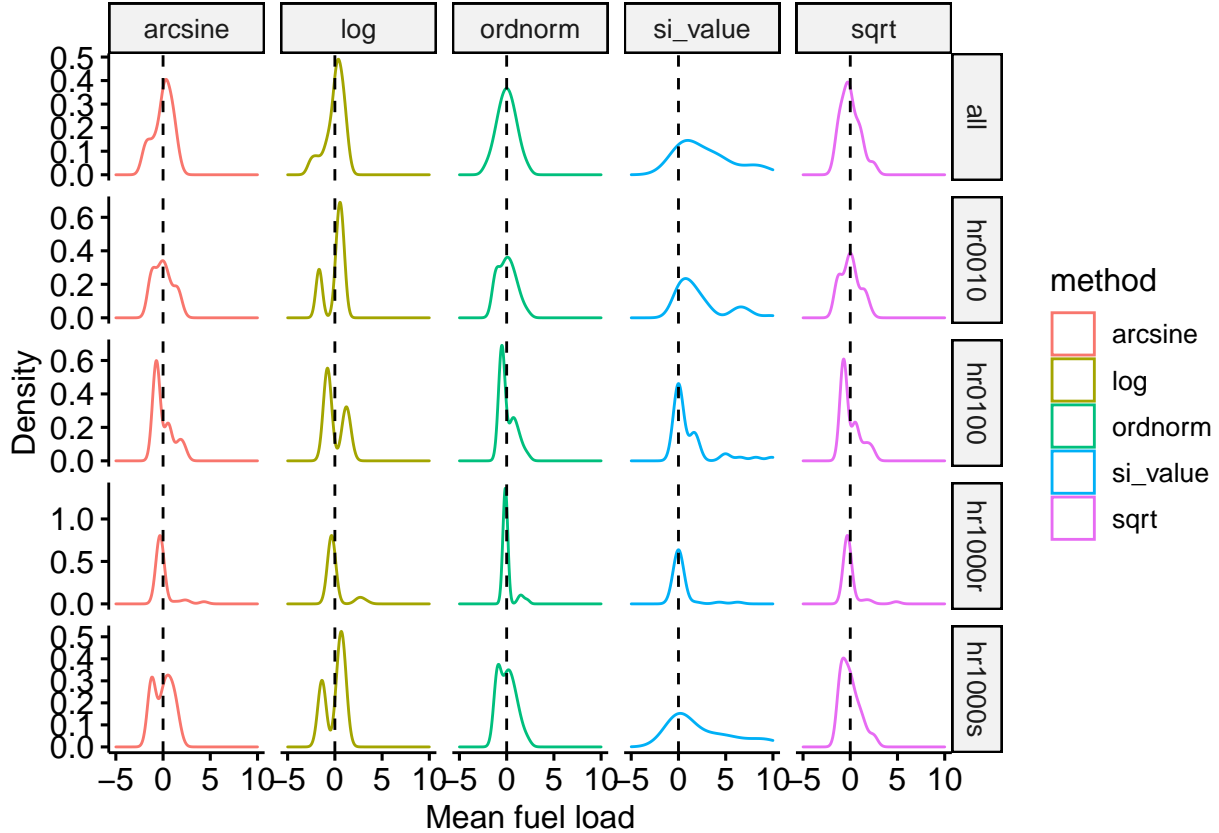
The transformed values for CWD by fuel class were normally distributed for more of the fuel class x year combinations; but still had 5 that were not normally distributed, as assessed by Shapiro-Wilk's test.

Total: arcsine, log, ordnorm

No transformation resulted in normal distribution for 10-hr (2017), 100-hr (2017, 2019, 2021)

1000-hr sound: none for 2016; ordnorm, sqrt for 2017, 2019, 2021; arcsine for 2017, 2019

fuel_class	time	arcsine	log	norm	ordnorm	si_value	sqrt	std	us_value
all	2016	TRUE	TRUE	TRUE	TRUE	NA	NA	NA	NA
all	2017	TRUE	TRUE	TRUE	TRUE	NA	TRUE	NA	NA
all	2019	TRUE	TRUE	TRUE	TRUE	NA	TRUE	NA	NA
all	2021	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
hr0010	2016	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
hr0010	2019	TRUE	NA	NA	TRUE	TRUE	NA	TRUE	TRUE
hr0010	2021	TRUE	NA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
hr0100	2016	NA	NA	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
hr1000s	2017	NA	NA	TRUE	TRUE	NA	TRUE	NA	NA
hr1000s	2019	TRUE	NA	TRUE	TRUE	NA	TRUE	NA	NA
hr1000s	2021	TRUE	NA	TRUE	TRUE	NA	TRUE	NA	NA



Normalize and standardize data SECTION IN PROGRESS

We applied an arcsine transformation to normalize the plot-level mean values for the 1000-hr rotten fuel class, calculated as $\log(x + \sqrt{x^2 + 1})$. The arcsine transformation (also called the arcsine square root transformation, or the angular transformation) was identified as the most suitable method using the R function `bestNormalize()` [bestNormalize package].

We applied an ordered quantile transformation the remaining subsets (total, and mean by fuel class for the 1-hr, 10-hr, 100-hr, and 1000-hr sound classes), calculated as:

$$g(x) = \psi^{-1} * ((\text{rank}(x) - .5) / (\text{length}(x)))$$

Where ψ refers to the standard normal cumulative distribution function, $\text{rank}(x)$ refers to each observation's rank, and $\text{length}(x)$ refers to the number of observations. The ordered quantile transformation is a rank-

based procedure by which the values of a vector are mapped to their percentile, which is then mapped to the same percentile of the normal distribution. Without the presence of ties, this essentially guarantees that the transformation leads to a uniform distribution.

All values were standardized upon normalization to have a mean of 0 and standard deviation of 1.

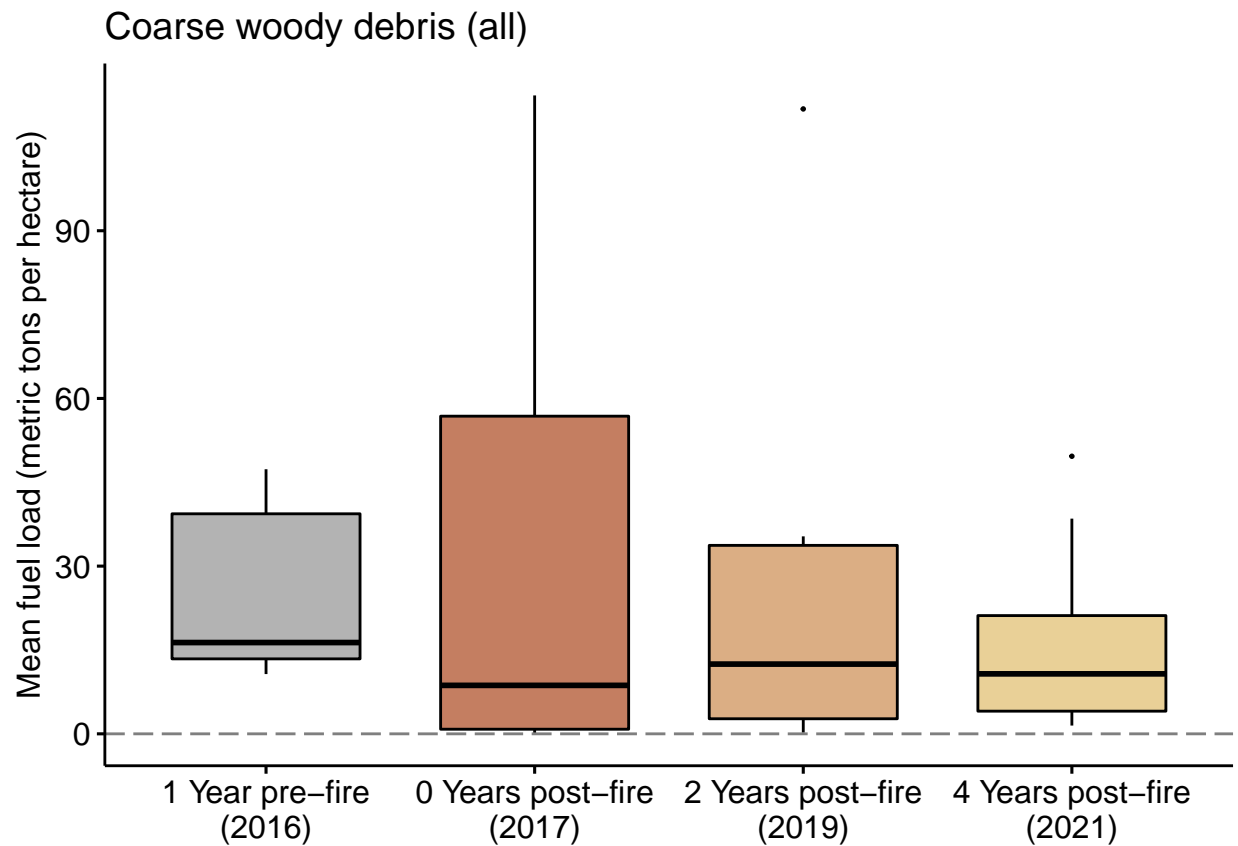
Total fuel load

Summary statistics for total fuel load by year

The following table summarizes the plot-level total amount of coarse woody debris for each time point.

fuel_class	time	units	mean	sd	n
All	2016	MT/ha	24.172	15.074	9
All	2017	MT/ha	29.139	40.550	9
All	2019	MT/ha	24.378	35.325	9
All	2021	MT/ha	16.704	17.012	9

Visualization of total fuel load by year



Main effect of year on total fuel load

We conducted a one-way repeated measures ANOVA to test for a main effect of year on fuel load (i.e., whether total fuel load was significantly different between the four time points).

fuel_class	method	effect	p_adj	p_adj_sig	statistic	d_fn	d_fd	ges	index_value
All	me	time	0.435	n.s.	0.817	1.54	12.34	0.042	value_norm

Pairwise comparison of total fuel load between years

fuel_class	method	group1	group2	p_adj	p_adj_sig	statistic	df	index_value
All	pwc	2016	2017	1	n.s.	0.966	8	value_norm
All	pwc	2016	2019	1	n.s.	1.318	8	value_norm
All	pwc	2016	2021	1	n.s.	1.404	8	value_norm
All	pwc	2017	2019	1	n.s.	-0.130	8	value_norm
All	pwc	2017	2021	1	n.s.	-0.200	8	value_norm
All	pwc	2019	2021	1	n.s.	-0.213	8	value_norm

Mean fuel load, by fuel class

Summary statistics for mean fuel load by fuel class and year

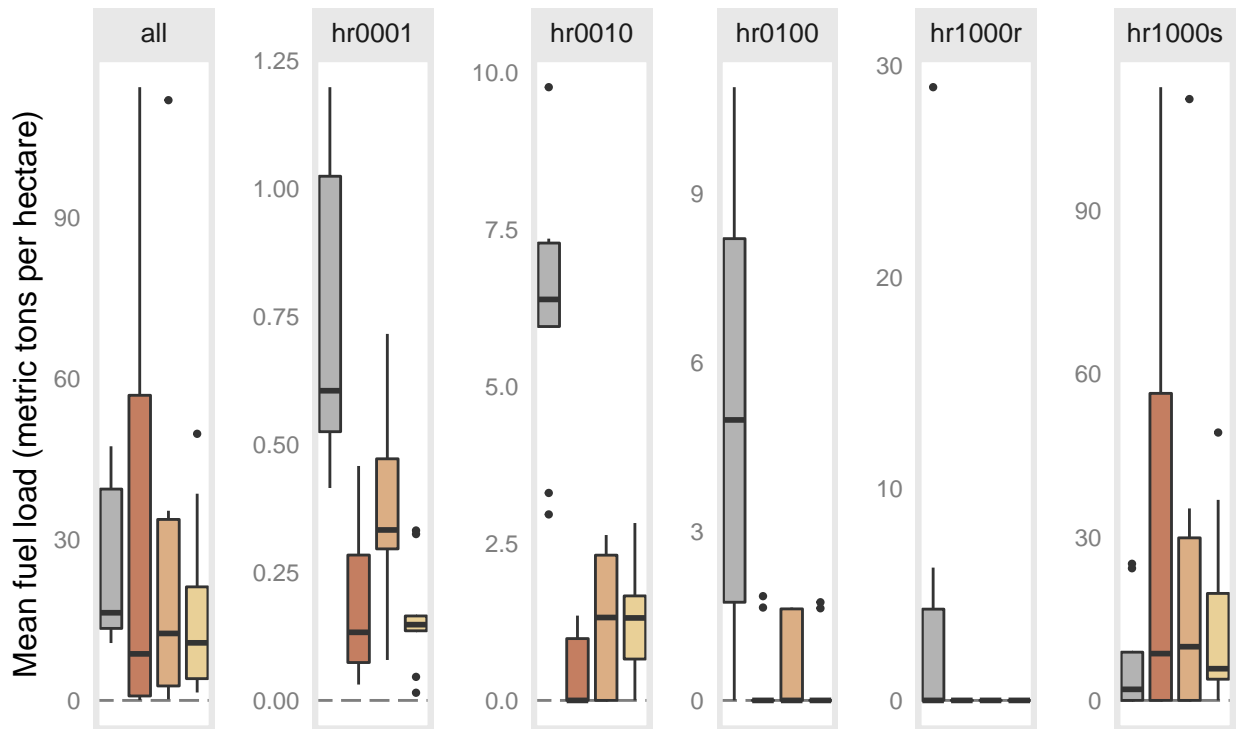
The following table summarizes the plot-level mean values for the five fuel classes at each time point.

lab_class	time	units	mean	sd	n
1-hr	2016	MT/ha	0.739	0.294	9
1-hr	2017	MT/ha	0.181	0.145	9
1-hr	2019	MT/ha	0.371	0.194	9
1-hr	2021	MT/ha	0.164	0.107	9
10-hr	2016	MT/ha	6.212	2.075	9
10-hr	2017	MT/ha	0.482	0.606	9
10-hr	2019	MT/ha	1.217	1.087	9
10-hr	2021	MT/ha	1.203	0.843	9
100-hr	2016	MT/ha	5.245	4.050	9
100-hr	2017	MT/ha	0.389	0.773	9
100-hr	2019	MT/ha	0.546	0.819	9
100-hr	2021	MT/ha	0.375	0.745	9
1000-hr rotten	2016	MT/ha	4.600	9.424	9
1000-hr rotten	2017	MT/ha	0.000	0.000	9
1000-hr rotten	2019	MT/ha	0.000	0.000	9
1000-hr rotten	2021	MT/ha	0.000	0.000	9
1000-hr sound	2016	MT/ha	7.375	10.300	9
1000-hr sound	2017	MT/ha	28.087	40.242	9
1000-hr sound	2019	MT/ha	22.245	35.521	9
1000-hr sound	2021	MT/ha	14.962	17.278	9

Visualization of mean fuel load by fuel class and year

A box plot of coarse woody debris by year and fuel class showed the post-fire trends differed among the five coarse woody debris fuel classes. [Note: The y-axis scale in the figure below differs by fuel class]

Timing 1-y pre-fire (2016) 0-y post-fire (2017) 2-y post-fire (2019) 4-y post-fire



Interaction between year and fuel class

We investigated whether there was a significant change in the plot-level fuel load over time when accounting for fuel class. A two-way repeated measures ANOVA was used to determine whether there was a significant interaction between year and fuel class on mean fuel load.

method	effect	p_adj	p_adj_sig	statistic	d_fn	d_fd	ges	index_value
interaction	time:fuel_class	6.99e-05	***	4.248	12	96	0.217	value_norm

Effect of treatment on each fuel class

fuel_class	method	effect	p_adj	p_adj_sig	statistic	d_fn	d
hr0010	me	time	3.80e-06	***	20.714	3.00	2
hr0001	me	time	2.43e-05	***	16.532	3.00	2
hr0100	me	time	5.00e-03	**	7.495	3.00	2
hr1000r	me	time	8.00e-02	n.s.	4.193	3.00	2
hr1000s	me	time	1.00e+00	n.s.	0.864	1.58	1

Pairwise comparisons of mean fuel load between years, by fuel class

fuel_class	method	group1	group2	p_adj	p_adj_sig	statistic	df	index_value
hr0001	pwc	2017	2019	0.003000	**	-5.749	8	value_norm
hr0001	pwc	2016	2021	0.005000	**	5.130	8	value_norm
hr0001	pwc	2016	2017	0.008000	**	4.790	8	value_norm
hr0001	pwc	2019	2021	0.026000	*	3.931	8	value_norm
hr0010	pwc	2016	2017	0.000572	***	7.168	8	value_norm
hr0010	pwc	2016	2021	0.001000	***	6.423	8	value_norm
hr0010	pwc	2016	2019	0.008000	**	4.772	8	value_norm
hr0100	pwc	2016	2021	0.047000	*	3.526	8	value_norm

1-hour

A post hoc pairwise comparison showed a significant difference in 1-hr fuel load between 2016-2017, 2016-2021, and 2017-2019 ($p < 0.01$); as well as 2019-2021 ($p < 0.05$). No other comparisons were significant.

10-hour

A post hoc pairwise comparison showed a significant difference in 10-hr fuel load between 2016-2017 ($p < 0.001$), 2016-2021 ($p < 0.01$), and 2016-2019 ($p < 0.05$). No other comparisons were significant.

100-hour

A post hoc pairwise comparison showed no significant difference in 100-hr fuel load between years 2016-2021 at a significance level of < 0.05 .

1000-hour rotten

Post hoc comparisons showed no significant difference in 1000-hr rotten fuel load between years at a significance level of < 0.05 .

1000-hour sound

Post hoc comparisons showed no significant difference in 1000-hr sound fuel load between years at a significance level of < 0.05 .