

Fuel analysis for Oak Symposium: coarse woody debris

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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?

Coarse woody debris data 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 five fuel classes within a plot: 1-hr, 10-hr, 100-hr, 1000-hr rotten, 1000-hr sound.

First, we calculated the plot-level mean ($n = 4$ quadrats) for each fuel class at each time point. A subset of the data frame with the plot-level mean for each fuel class by year is shown below.

fuel_type	fuel_class	plot_id	year	value
Coarse woody debris	1-hr	RxF01	2016	0.487
Coarse woody debris	10-hr	RxF01	2016	3.281
Coarse woody debris	100-hr	RxF01	2016	2.214
Coarse woody debris	1000-hr sound	RxF01	2016	0.000
Coarse woody debris	1000-hr rotten	RxF01	2016	0.000
Coarse woody debris	1-hr	RxF02	2016	0.347

Next, we summed the means for all fuel classes to find the plot-level total for coarse woody debris at each time point. Below is a subset of the data frame for the plot-level values of coarse woody debris by year.

fuel_type	fuel_class	plot_id	year	value
Coarse woody debris	All	RxF01	2016	5.981
Coarse woody debris	All	RxF02	2016	7.282
Coarse woody debris	All	RxF03	2016	5.147
Coarse woody debris	All	RxF04	2016	17.556
Coarse woody debris	All	RxF05	2016	4.768
Coarse woody debris	All	RxF06	2016	21.112

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.

Q1: Did total fuel load differ between years?

The first question we asked was whether there was a significant main effect of year on total fuel load. A one-way repeated measures ANOVA was used to determine whether the fuel load was significantly different between the four time points.

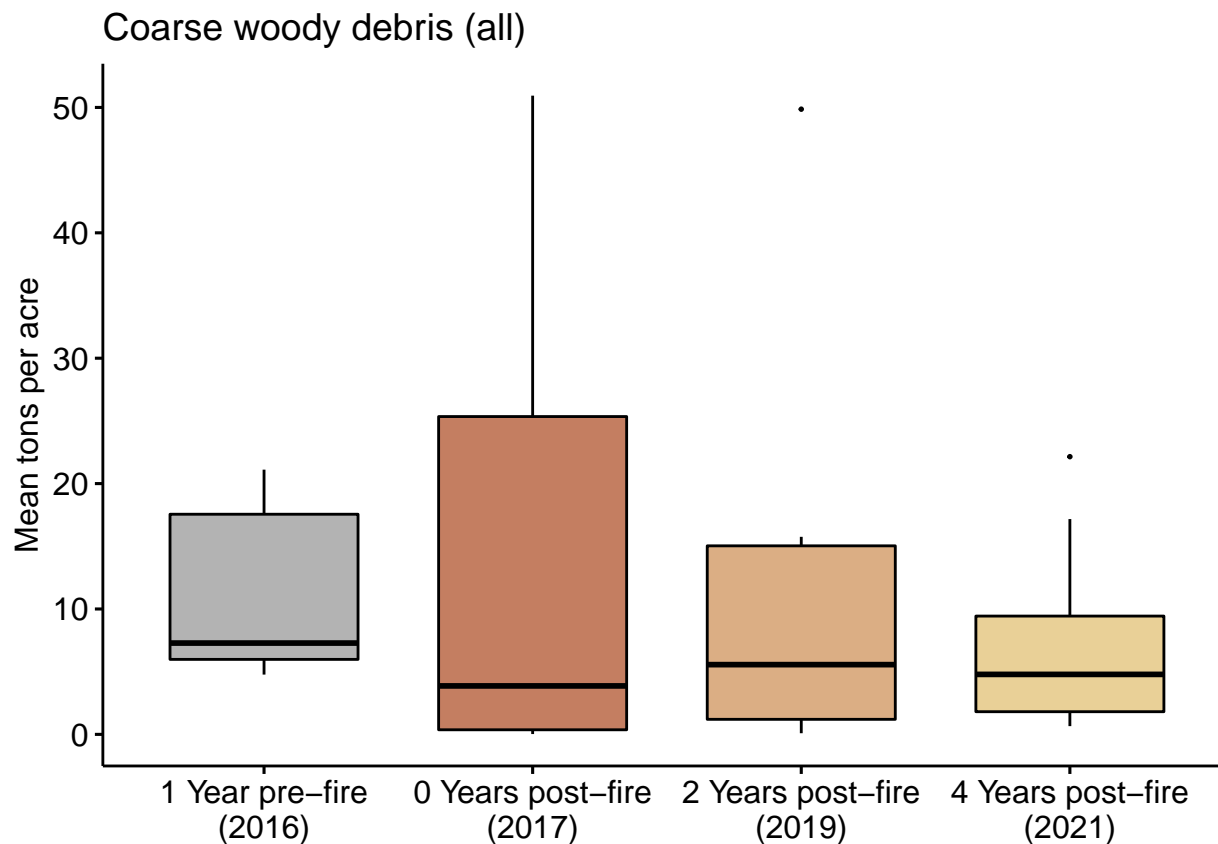
Summary statistics for the plot-level total amount of coarse woody debris by year

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

data_type	fuel_class	year	mean	sd	n
Coarse woody debris	All	2016	10.781	6.724	9
Coarse woody debris	All	2017	12.997	18.087	9
Coarse woody debris	All	2019	10.873	15.756	9
Coarse woody debris	All	2021	7.451	7.588	9

Visualization of the plot-level total amount of coarse woody debris by year

A boxplot of total coarse woody debris by year showed lower values in post-fire years. Specifically, we observed a decrease in the depth of all coarse woody debris immediately following the fire (2017; 0-y post-fire). Variance in 2017 was much greater than at any other time point. The mean depth of coarse woody debris did not return to pre-fire levels in subsequent years. However, the fuel load increased from 2017 levels by 2019, and showed little change between 2019 and 2021.



Check assumptions

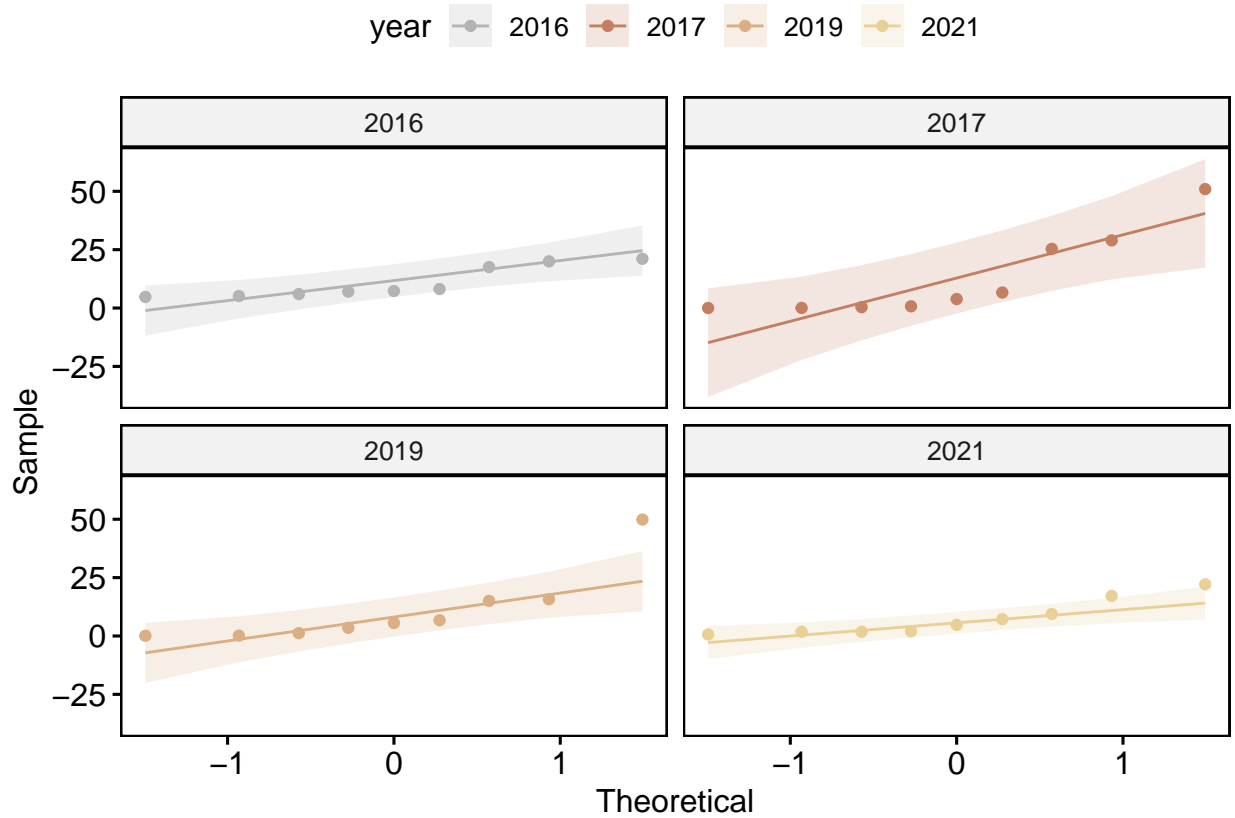
Check for outliers There were no extreme outliers in the data set.

data_type	fuel_class	year	plot_id	value	is_outlier	is_extreme
Coarse woody debris	All	2019	RxF01	49.861	TRUE	FALSE
Coarse woody debris	All	2021	RxF07	22.148	TRUE	FALSE

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

data_type	fuel_class	year	is_normal	p	statistic
Coarse woody debris	All	2016	FALSE	0.0133182	0.784
Coarse woody debris	All	2017	FALSE	0.0090478	0.769
Coarse woody debris	All	2019	FALSE	0.0016027	0.705

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

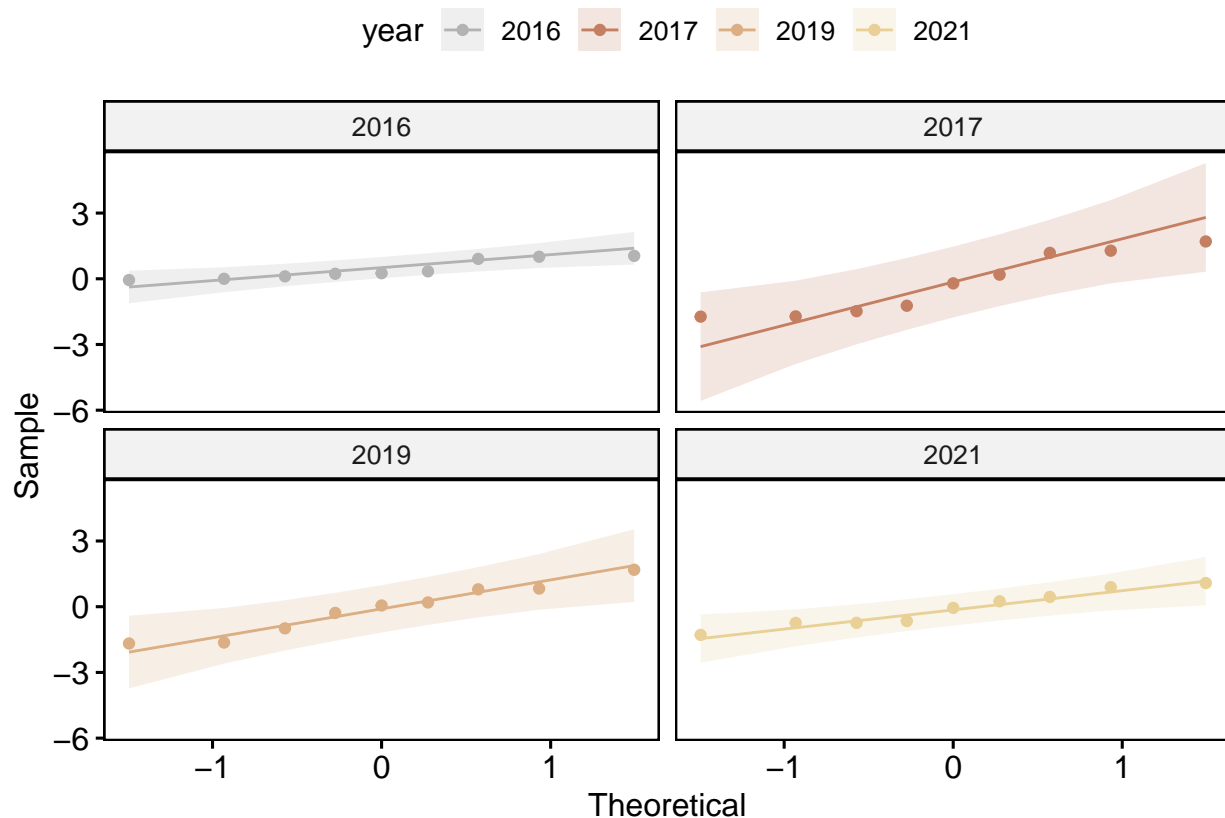


Normalize data and repeat checks We applied an arcsine transformation to normalize the plot-level values for total coarse woody debris, calculated as $\log(x + \sqrt{x^2 + 1})$. The arcsine transformation (also called the arcsine square root transformation, or the angular transformation) was identified as the most suitable method using the R function `bestNormalize()` [bestNormalize package]. Values were standardized upon normalization to have a mean of 0 and standard deviation of 1.

The transformed values for total coarse woody debris were normally distributed at each time point ($p > 0.05$), as assessed by Shapiro-Wilk's test.

data_type	fuel_class	year	is_normal	p	statistic
Coarse woody debris	All	2016	TRUE	0.0705051	0.848
Coarse woody debris	All	2017	TRUE	0.1501308	0.878
Coarse woody debris	All	2019	TRUE	0.6898519	0.950
Coarse woody debris	All	2021	TRUE	0.6270983	0.944

All the points on the below QQ plot fell approximately along the reference line, we could assume normality.



The two outliers (not extreme) detected in the untransformed data were absent after the transformation was applied.

data_type	fuel_class	year	plot_id	value	is_outlier	is_extreme
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Repeated measures ANOVA test

We found no significant main effect of year on the plot-level total for coarse woody debris ($p = 0.359$).

data_type	fuel_class	effect	p_adj	p_adj_sig	statistic	d_fn	d_fd	ges	method
Coarse woody debris	All	year	0.297	n.s.	1.306	1.7	13.56	0.065	me

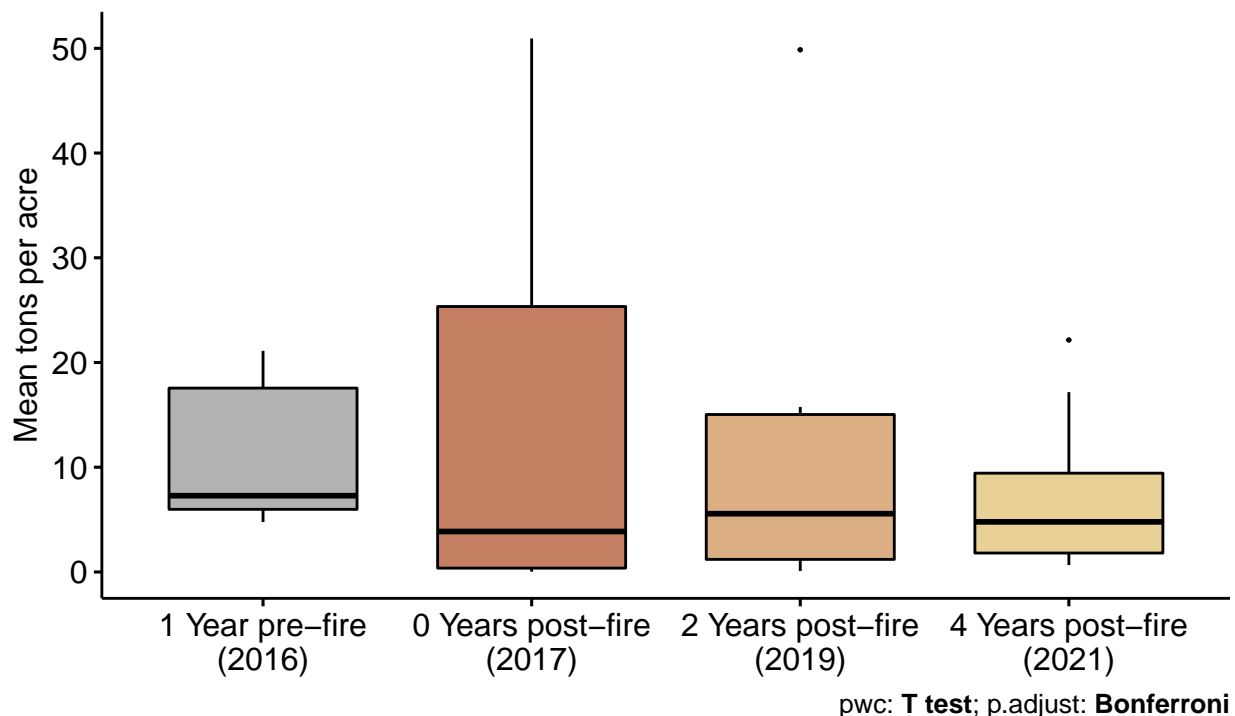
Post hoc tests

We conducted post hoc pairwise comparisons between the levels of the within-subjects factor (here, year). The result of paired t-tests between years showed no significant difference in fuel load between years at a significance level of < 0.05 . This finding is consistent with the lack of main effect found for year.

The results from the pairwise comparisons are shown below as (1) a boxplot of total coarse woody debris by year (the lack of p-values reflects the absence of significant comparisons), and (2) a table of test results.

Coarse woody debris (all)

Anova, $F(1.7,13.56) = 1.31$, $p = 0.3$, $\eta_g^2 = 0.06$



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Coarse woody debris	All	2016	2021	0.738	ns	1.723	8	pwc
Coarse woody debris	All	2016	2017	1.000	ns	1.387	8	pwc
Coarse woody debris	All	2016	2019	1.000	ns	1.431	8	pwc
Coarse woody debris	All	2017	2019	1.000	ns	-0.685	8	pwc
Coarse woody debris	All	2017	2021	1.000	ns	-0.319	8	pwc
Coarse woody debris	All	2019	2021	1.000	ns	-0.072	8	pwc

Q2: Did fuel load differ between years by fuel class?

Next, we investigated whether there was a significant change in 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 fuel load.

Here, the effect of year on fuel load was our focal variable of primary concern. However, the effect year may differ between fuel classes, so fuel_class was considered a moderator variable.

Summary statistics for coarse woody debris by year and fuel class

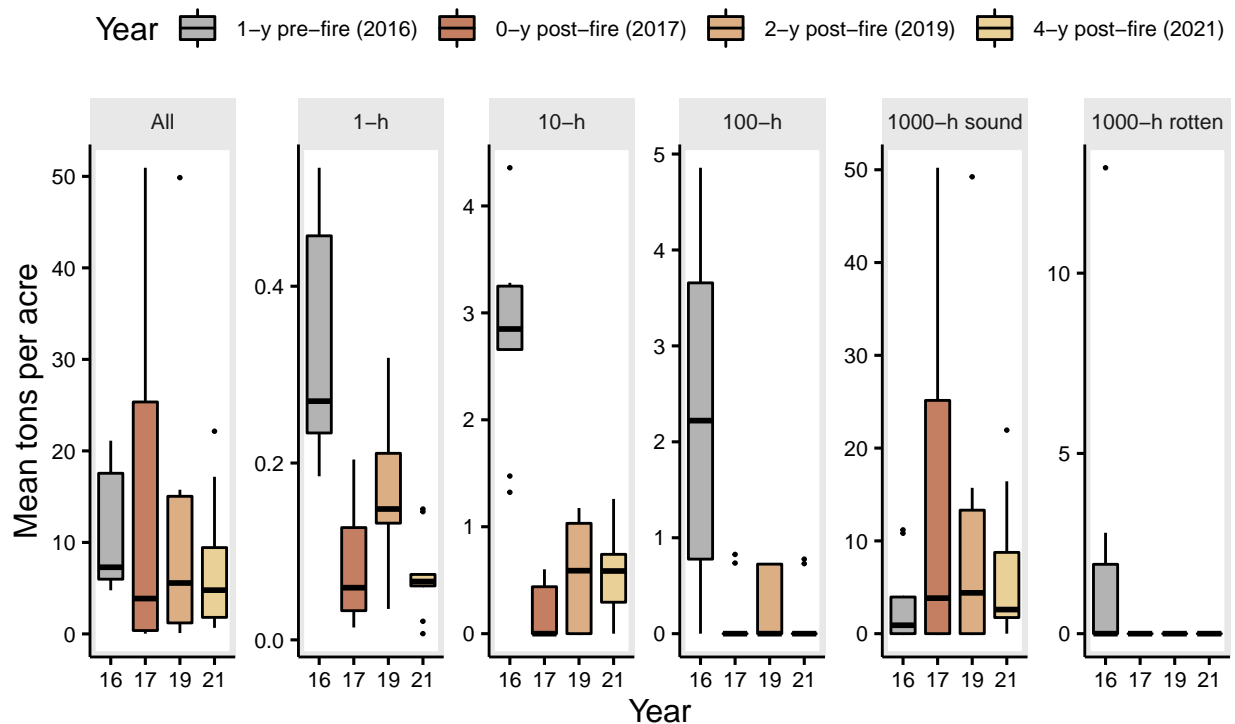
The following table summarizes coarse woody debris by class for each time point.

data_type	fuel_class	statistic	2016	2017	2019	2021
Coarse woody debris	hr0001	mean	0.330	0.081	0.165	0.073
Coarse woody debris	hr0001	sd	0.131	0.065	0.086	0.048
Coarse woody debris	hr0010	mean	2.771	0.215	0.543	0.537
Coarse woody debris	hr0010	sd	0.925	0.270	0.485	0.376
Coarse woody debris	hr0100	mean	2.339	0.174	0.244	0.167
Coarse woody debris	hr0100	sd	1.807	0.345	0.365	0.332
Coarse woody debris	hr1000r	mean	3.290	12.528	9.922	6.673
Coarse woody debris	hr1000r	sd	4.594	17.949	15.843	7.707
Coarse woody debris	hr1000s	mean	2.052	0.000	0.000	0.000
Coarse woody debris	hr1000s	sd	4.203	0.000	0.000	0.000

Visualization of coarse woody debris by year and fuel class

A boxplot 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]

coarse woody debris, by fuel class



Note: y-axis scale differs by fuel class

We observed a decrease in fuel load immediately after the fire (2017; 0-y post-fire) for all classes of coarse woody debris except 1000-hr sound. Specifically, the fuel load in 2017 for 1-hr, 10-hr, 100-hr, and 1000-hr rotten classes was much lower than pre-fire values; variance was unsurprising. Further, mean values for these four classes remained lower than 2016 values for all post-fire years.

The mean for 1000-hr sound fuels increased immediately after the fire and remained greater than 2016 values for all post-fire years. Variance for this fuel class was elevated in 2017. The temporal trend for all coarse woody debris was more similar to that for the 1000-hr sound fuel class, and showed less similarity to those for other classes. These results suggest that 1000-hr sound fuel was an influential driver of the post-fire patterns observed for all coarse woody debris.

Check assumptions

Check for outliers There were nine extreme outliers in the data set. Most outliers ($n = 6$) were from the year 2021. The 1-hr and 100-hr classes each had 4 outliers.

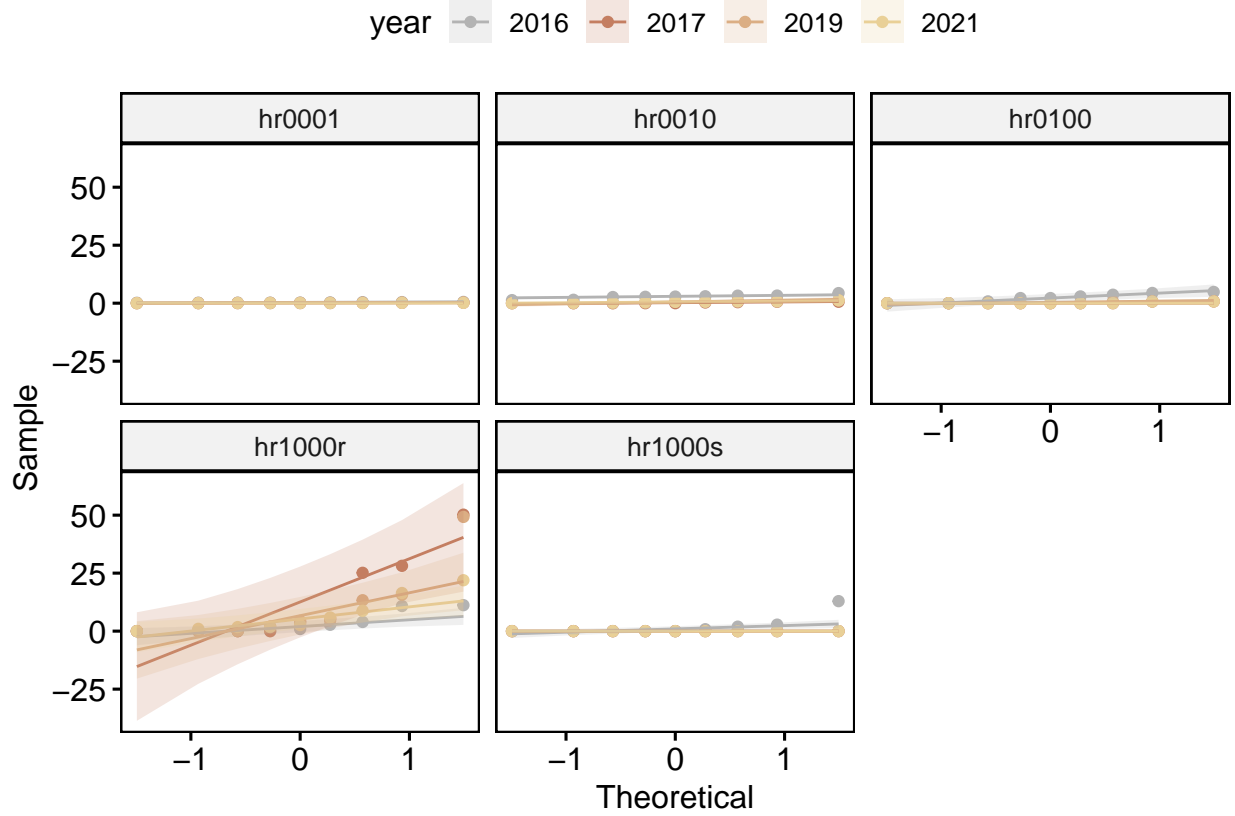
data_type	fuel_class	year	plot_id	value	is_outlier	is_extreme
Coarse woody debris	hr1000s	2016	RxF04	12.924	TRUE	TRUE
Coarse woody debris	hr0100	2017	RxF03	0.736	TRUE	TRUE
Coarse woody debris	hr0100	2017	RxF08	0.826	TRUE	TRUE
Coarse woody debris	hr0001	2021	RxF03	0.007	TRUE	TRUE
Coarse woody debris	hr0001	2021	RxF04	0.145	TRUE	TRUE
Coarse woody debris	hr0001	2021	RxF05	0.148	TRUE	TRUE
Coarse woody debris	hr0001	2021	RxF08	0.021	TRUE	TRUE
Coarse woody debris	hr0100	2021	RxF04	0.730	TRUE	TRUE
Coarse woody debris	hr0100	2021	RxF05	0.777	TRUE	TRUE

Check for normality Note: The data for the 1000-hr sound 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 sound 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; hr1000s is excluded). Four combinations included the 1000-hr rotten fuel class; three included year 2017.

data_type	fuel_class	year	is_normal	p	statistic
Coarse woody debris	hr0010	2017	FALSE	0.0059166	0.753
Coarse woody debris	hr0100	2017	FALSE	0.0000258	0.551
Coarse woody debris	hr0100	2019	FALSE	0.0001664	0.620
Coarse woody debris	hr0100	2021	FALSE	0.0000215	0.545
Coarse woody debris	hr1000r	2016	FALSE	0.0036207	0.735
Coarse woody debris	hr1000r	2017	FALSE	0.0066142	0.757
Coarse woody debris	hr1000r	2019	FALSE	0.0008514	0.681
Coarse woody debris	hr1000r	2021	FALSE	0.0319642	0.817

Overall, the distribution of values 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.



Normalize data and repeat checks We subset the plot-level values for coarse woody debris by fuel class, then applied an ordered quantile transformation to normalize the plot-level values for total coarse woody debris, 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. Values were standardized by fuel class upon normalization to have a mean of 0 and standard deviation of 1.

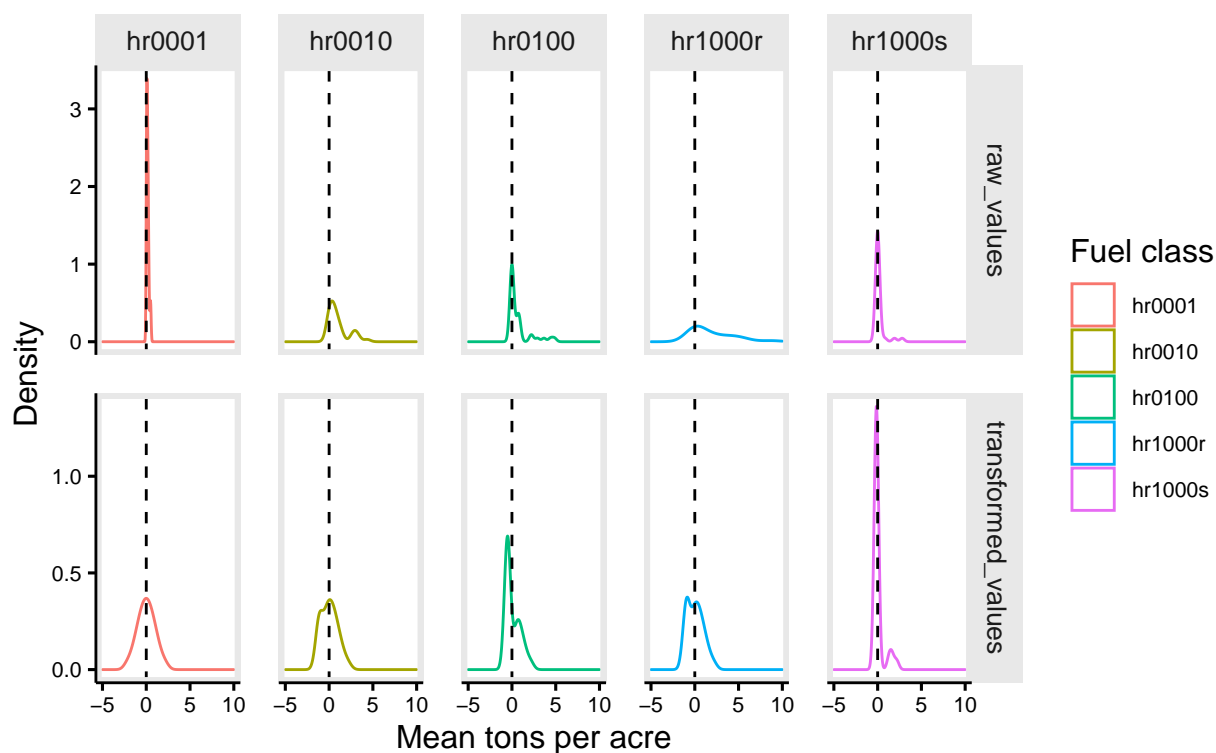
The following table lists the transformation applied to each fuel class, as well as the mean and standard deviation (sd) for raw and transformed values. Note the untransformed mean for 1000-hr rotten is >8 , a much larger value compared to those of the other classes that range from 0.162 to 1.016.

```
## `summarise()` has grouped output by 'fuel_class'. You can override using the
## `.groups` argument.
```

metric	statistic	hr0001	hr0010	hr0100	hr1000r	hr1000s
value	mean	0.000	0.027	0.069	0.038	0.062
value	sd	0.996	0.934	0.807	0.909	0.590
value_raw	mean	0.162	1.016	0.731	8.103	0.513
value_raw	sd	0.135	1.171	1.310	12.719	2.202

The following plot shows the raw (untransformed) values on the left and the transformed values on the right.

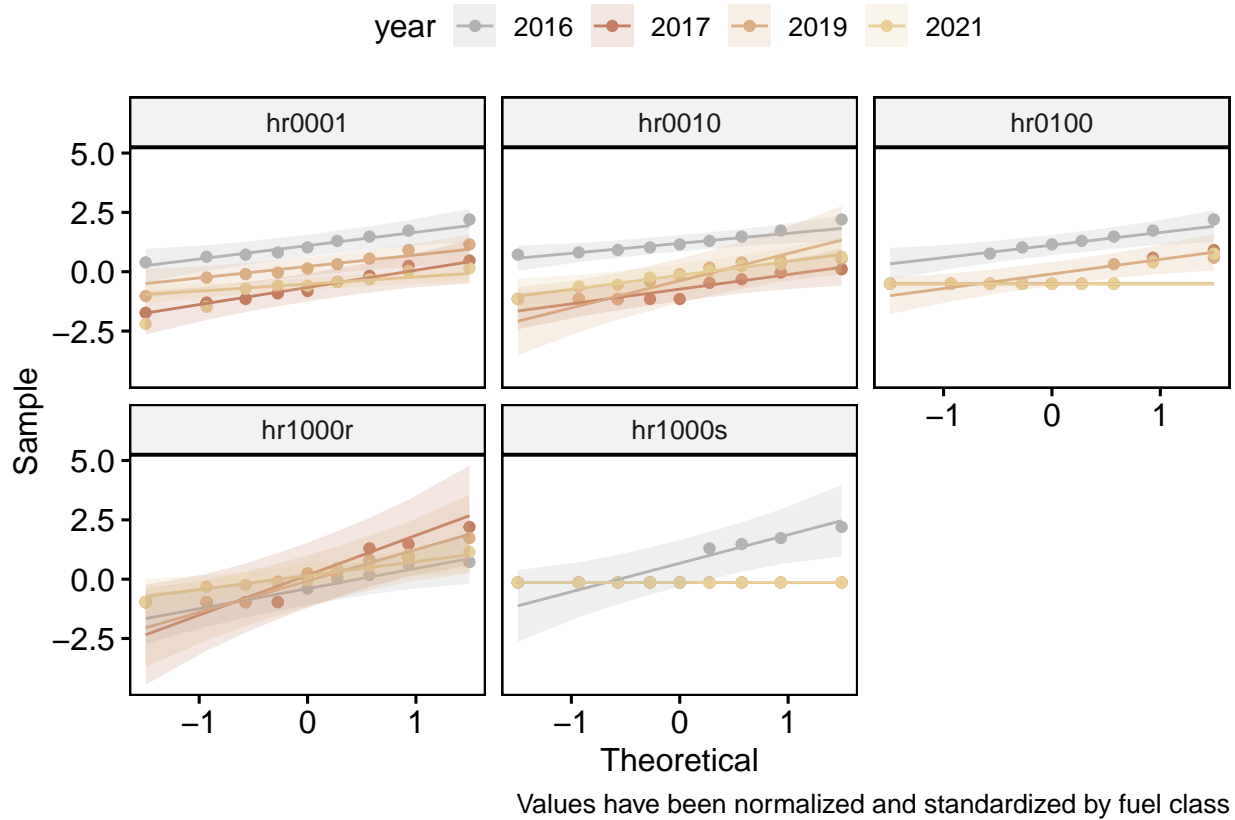
Distribution of values, by fuel class and transformation



The transformed values for coarse woody debris 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.

data_type	fuel_class	year	is_normal	p	statistic
Coarse woody debris	hr0010	2017	FALSE	0.0090893	0.769
Coarse woody debris	hr0100	2017	FALSE	0.0000366	0.564
Coarse woody debris	hr0100	2019	FALSE	0.0005615	0.666
Coarse woody debris	hr0100	2021	FALSE	0.0000412	0.569
Coarse woody debris	hr1000r	2016	FALSE	0.0479994	0.833

However, the points on the QQ plot were mostly near the reference line, suggesting an approximately normal-ish distribution.



All but one of the nine outliers detected in the untransformed data were absent after the transformation was applied.

data_type	fuel_class	year	plot_id	value	is_outlier	is_extreme
Coarse woody debris	hr0001	2021	RxF03	-2.200411	TRUE	TRUE

Repeated measures ANOVA test

There was a statistically significant two-way interaction between coarse woody debris class and year, $F(12, 96) = 5.302$, $p\text{-adj.} = 2.6\text{e-}06$, $\text{ges} = 0.242$. A significant two-way interaction indicates that the impact of fuel class on fuel load depends on year (and vice versa).

data_type	effect	p_adj	p_adj_sig	statistic	d_fn	d_fd	ges	method
Coarse woody debris	year	1.1e-06	***	22.596	3	24	0.298	aov2
Coarse woody debris	fuel_class:year	2.6e-06	***	5.302	12	96	0.242	aov2
Coarse woody debris	fuel_class	1.0e+00	n.s.	0.043	4	32	0.002	aov2

Post hoc tests

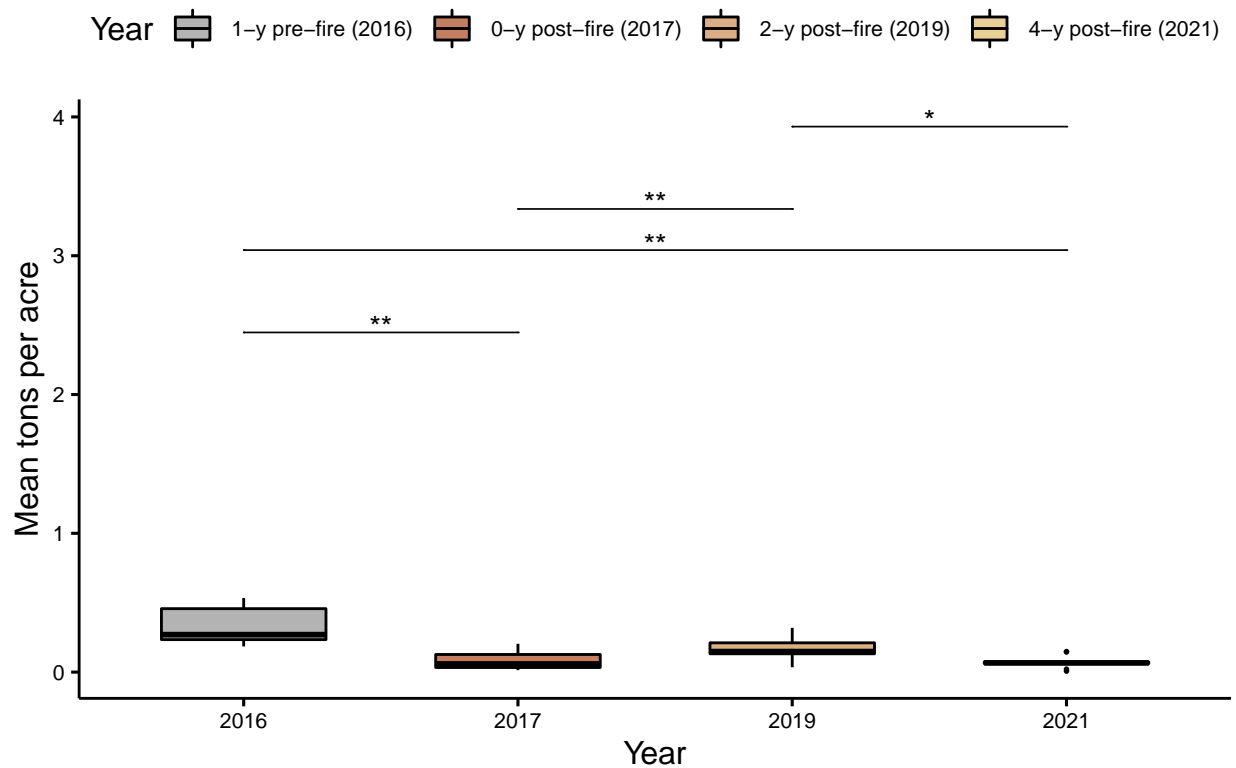
We found a significant main effect of year on fuel load for 1-hr, 10-hr ($p < 0.001$), 100-hr ($p < 0.01$), and 1000-hr sound ($p < 0.05$) fuel classes. No significant effect of year on fuel load was found for the 1000-hr sound class. One thing the pairwise comparison by fuel class had in common: For the classes with a significant main effect of year on fuel load, the fuel load in 2016 was significantly different from that in 2021.

data_type	fuel_class	effect	p_adj	p_adj_sig	statistic	d_fn	d_fd	ges	method
Coarse woody debris	hr0010	year	7.00e-06	***	19.277	3.00	24.00	0.647	me
Coarse woody debris	hr0001	year	2.55e-05	***	16.443	3.00	24.00	0.576	me
Coarse woody debris	hr0100	year	5.00e-03	**	7.495	3.00	24.00	0.418	me
Coarse woody debris	hr1000s	year	1.50e-02	*	6.023	3.00	24.00	0.361	me
Coarse woody debris	hr1000r	year	1.00e+00	n.s.	0.864	1.58	12.64	0.048	me

The following sections present the results from post hoc tests by fuel class for (1) the main effect of fuel class on fuel load at each time point, and (2) significant pairwise differences between years.

1-hour vs. Year 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.

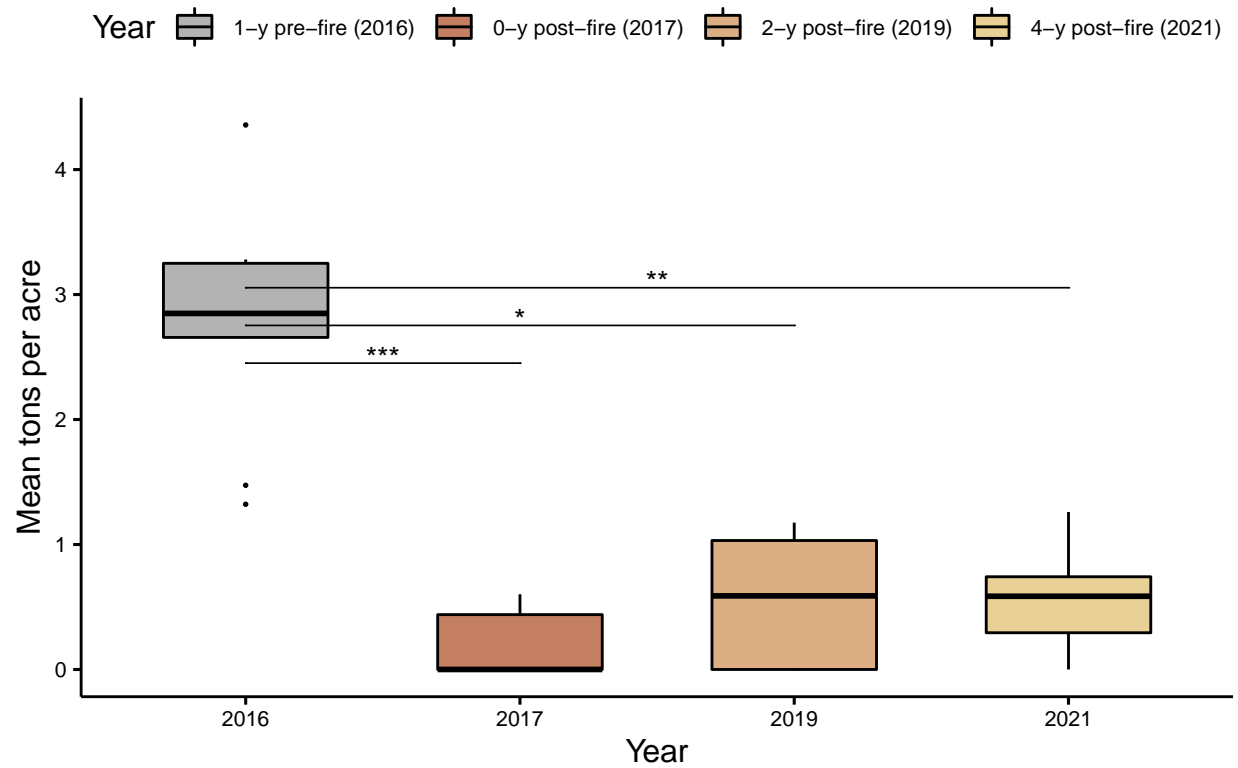
1-hr



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Coarse woody debris	1-hr	2017	2019	0.003	**	-5.613	8	pwc
Coarse woody debris	1-hr	2016	2021	0.006	**	5.076	8	pwc
Coarse woody debris	1-hr	2016	2017	0.008	**	4.812	8	pwc
Coarse woody debris	1-hr	2019	2021	0.028	*	3.877	8	pwc
Coarse woody debris	1-hr	2016	2019	0.158	ns	2.720	8	pwc
Coarse woody debris	1-hr	2017	2021	1.000	ns	0.143	8	pwc

10-hour vs. Year 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.

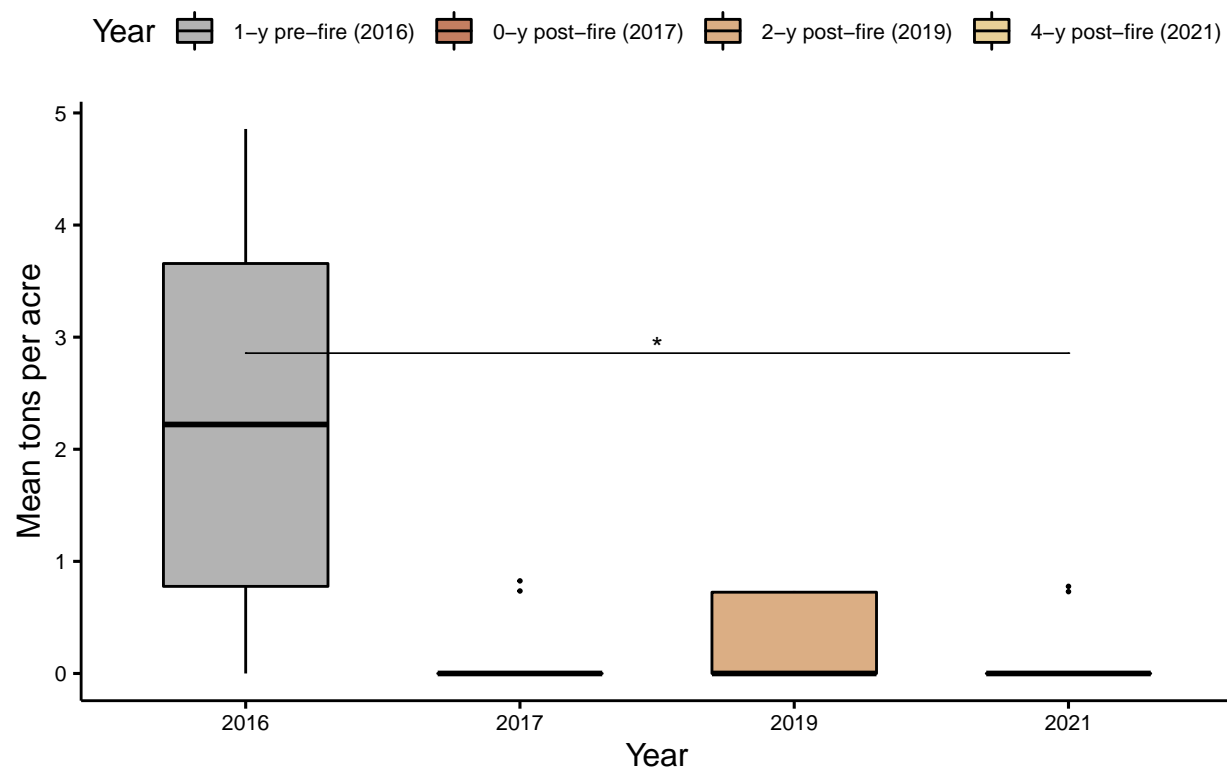
10-hr



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Coarse woody debris	10-hr	2016	2017	0.000282	***	7.918	8	pwc
Coarse woody debris	10-hr	2016	2021	0.001000	**	6.353	8	pwc
Coarse woody debris	10-hr	2016	2019	0.012000	*	4.503	8	pwc
Coarse woody debris	10-hr	2017	2021	0.248000	ns	-2.428	8	pwc
Coarse woody debris	10-hr	2017	2019	0.416000	ns	-2.097	8	pwc
Coarse woody debris	10-hr	2019	2021	1.000000	ns	-0.260	8	pwc

100-hour vs. Year 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 .

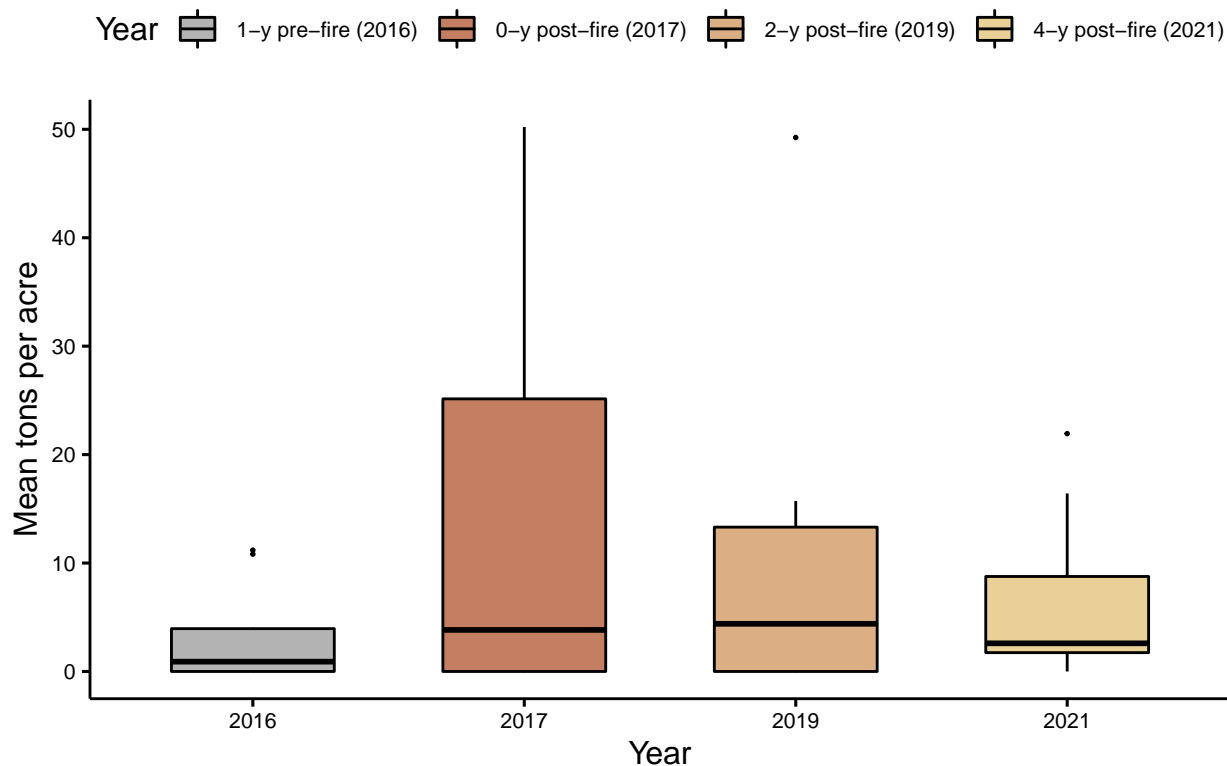
100-hr



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Coarse woody debris	100-hr	2016	2021	0.047	*	3.526	8	pwc
Coarse woody debris	100-hr	2016	2017	0.062	ns	3.336	8	pwc
Coarse woody debris	100-hr	2016	2019	0.094	ns	3.057	8	pwc
Coarse woody debris	100-hr	2017	2019	1.000	ns	-0.189	8	pwc
Coarse woody debris	100-hr	2017	2021	1.000	ns	0.137	8	pwc
Coarse woody debris	100-hr	2019	2021	1.000	ns	0.369	8	pwc

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

1000-hr sound

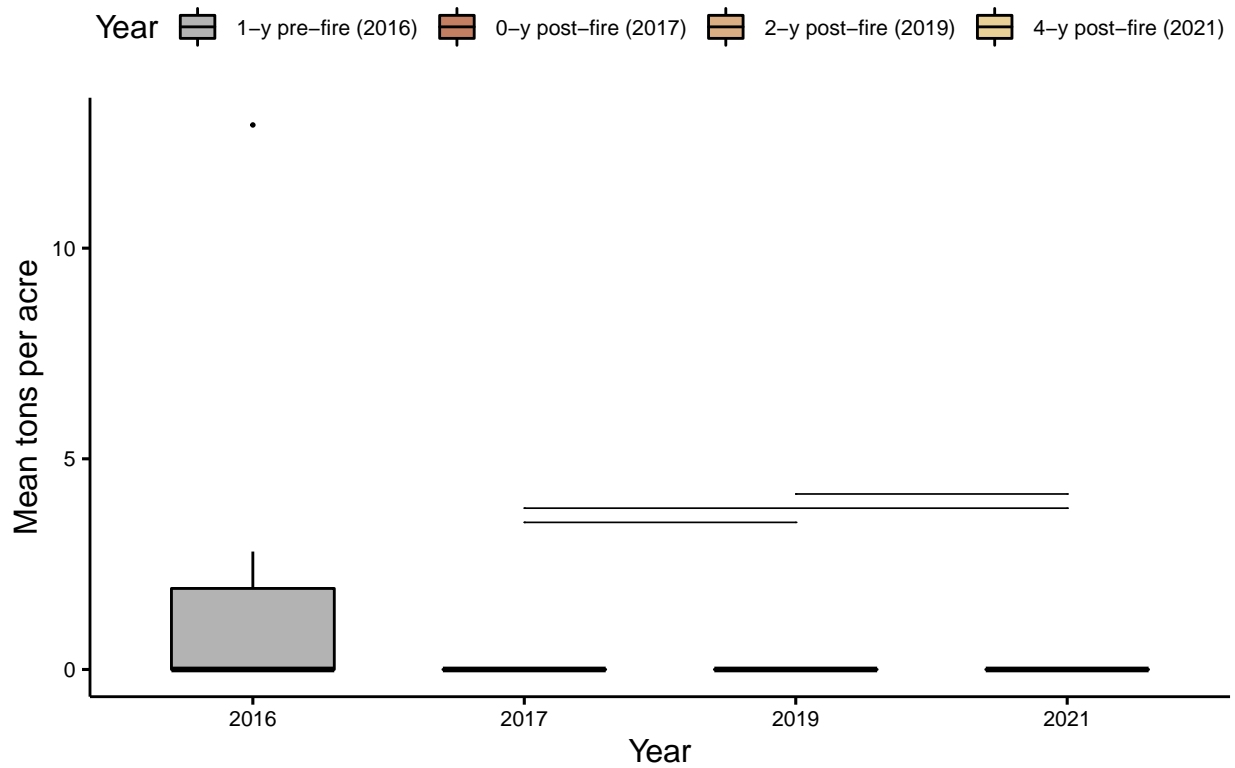


data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Coarse woody debris	1000-hr sound	2016	2017	1	ns	-0.999	8	pwc
Coarse woody debris	1000-hr sound	2016	2019	1	ns	-1.012	8	pwc
Coarse woody debris	1000-hr sound	2016	2021	1	ns	-1.494	8	pwc
Coarse woody debris	1000-hr sound	2017	2019	1	ns	0.454	8	pwc
Coarse woody debris	1000-hr sound	2017	2021	1	ns	0.047	8	pwc
Coarse woody debris	1000-hr sound	2019	2021	1	ns	-0.181	8	pwc

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

Note: The comparison lines in the plot for 1000-hour sound do not indicate significance. They are a flaw caused by NaN values in the significance test result.

1000-hr rotten



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Coarse woody debris	1000-hr rotten	2016	2017	0.119	ns	2.454	8	pwc
Coarse woody debris	1000-hr rotten	2016	2019	0.119	ns	2.454	8	pwc
Coarse woody debris	1000-hr rotten	2016	2021	0.119	ns	2.454	8	pwc
Coarse woody debris	1000-hr rotten	2017	2019	NaN		NaN	8	pwc
Coarse woody debris	1000-hr rotten	2017	2021	NaN		NaN	8	pwc
Coarse woody debris	1000-hr rotten	2019	2021	NaN		NaN	8	pwc

Date of last revision
2022-10-25
