Fuel analysis for Oak Symposium: Downed woody debris

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Overview

The aim of this research was to understand the impact of prescribed fire on fuel loads over time. Our objective was to evaluate the impact of prescribed fire on downed woody debris fuel loads over time (1-hr, 10-hr, 100-hr, 1000-hr rotten, 1000-hr sound). To meet this objective, we compared the pre- and post-fire fuel levels 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). Each time point had 18 data points for downed woody debris measurements (9 plots x 2 transects x 1 quadrat).

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

1. Did total fuel load differ between years?

2. Did fuel load differ between years by fuel class? If so, which years are different?

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 + 1.5xIQR or below Q1 - 1.5xIQR are considered as outliers. Values above Q3 + 3xIQR or below Q1 - 3xIQR 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.

Data frames To answer these questions, we calculated the total amount of downed woody debris within each plot. We defined "total (or all) downed 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. Because there were two transects with one quadrats per plot, we used the plot-level mean for each fuel class at each time point (n = 4 quadrats). 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
Downed woody debris	1-hr	RxF01	2016	0.487
Downed woody debris	10-hr	RxF01	2016	3.281
Downed woody debris	100-hr	RxF01	2016	2.214
Downed woody debris	1000-hr sound	RxF01	2016	0.000
Downed woody debris	1000-hr rotten	RxF01	2016	0.000
Downed woody debris	1-hr	RxF02	2016	0.347

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

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

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 (plot mean). A one-way repeated measures ANOVA was used to determine whether the mean fuel load was significantly different between the four time points.

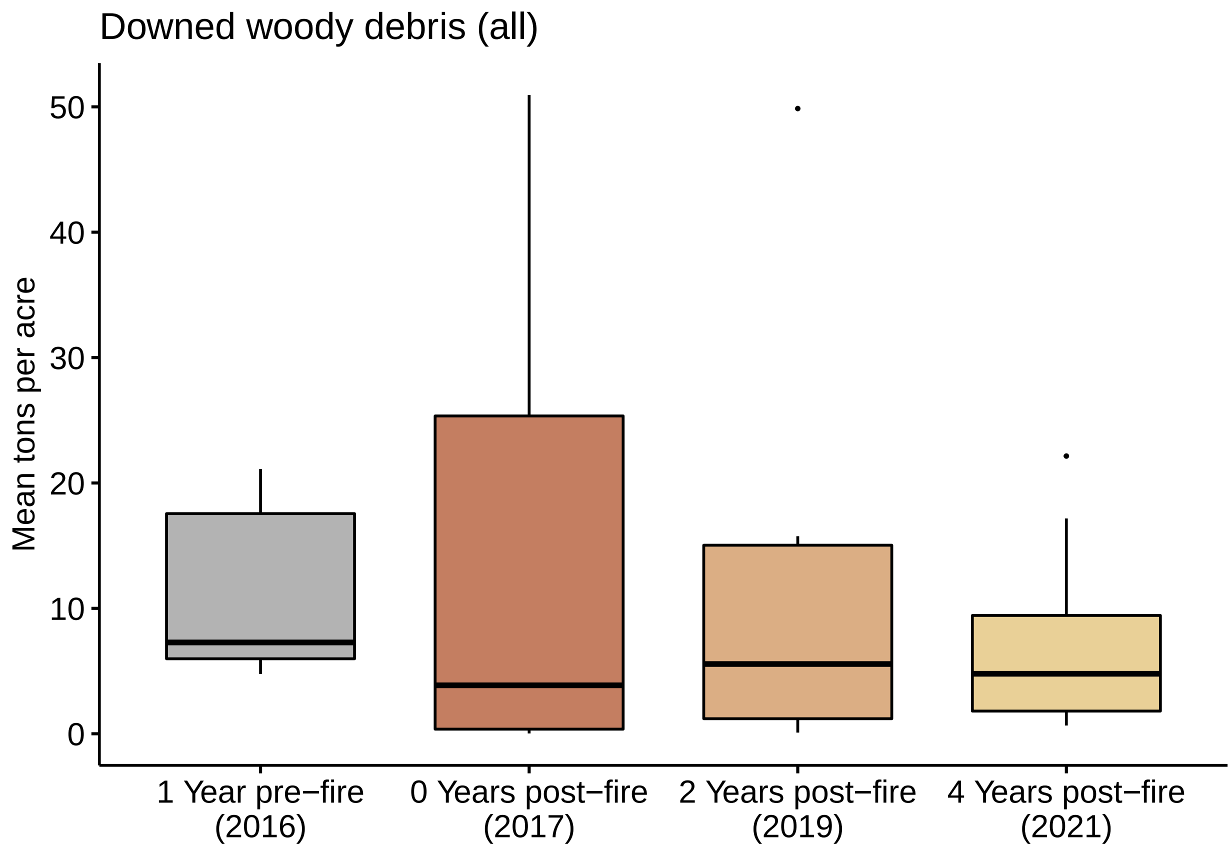
Summary statistics for the plot-level total amount of downed woody debris by year

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

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

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

A boxplot of total downed woody debris by year showed lower values in post-fire years. Specifically, we observed a decrease in the depth of all downed 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 downed 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

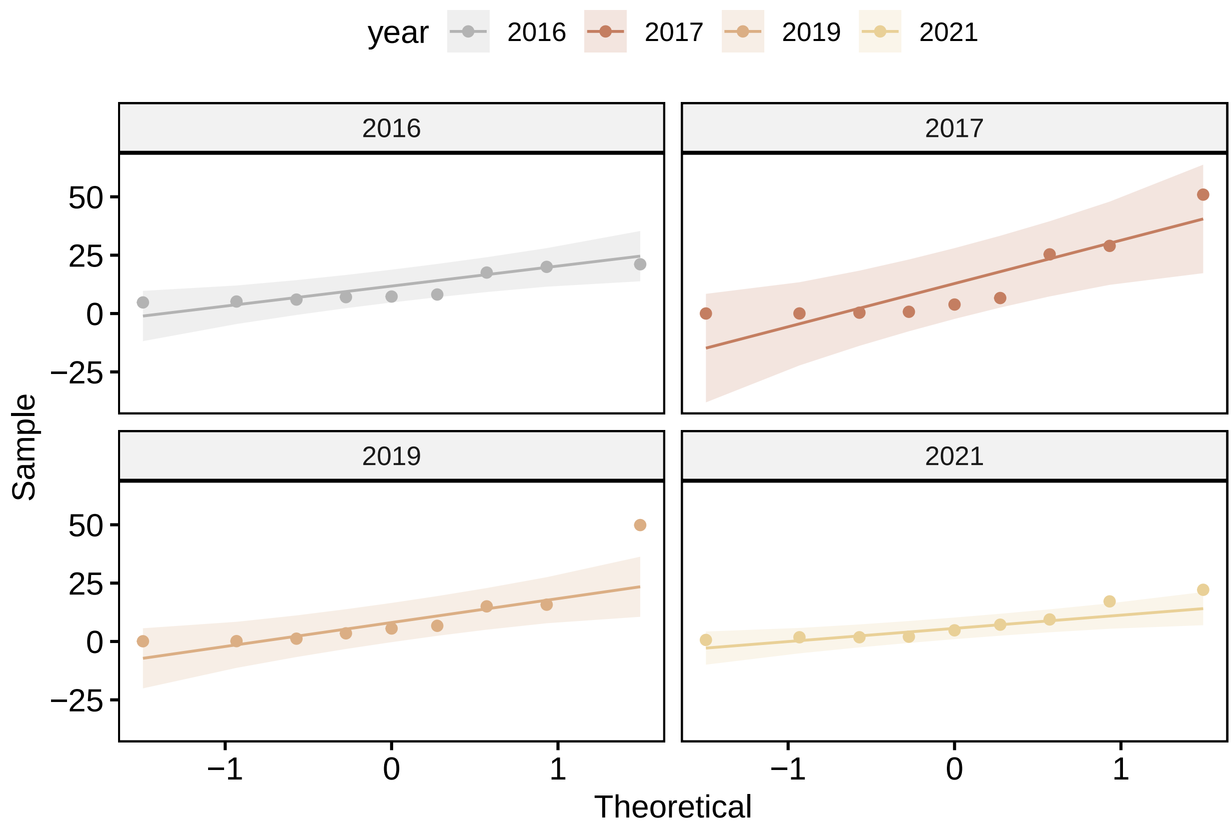
Check for outliers There were no extreme outliers in the data set.

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

Check for normality Plot-level values for downed 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
Downed woody debris	All	2016	FALSE	0.0133182	0.784
Downed woody debris	All	2017	FALSE	0.0090478	0.769
Downed woody debris	All	2019	FALSE	0.0016027	0.705

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

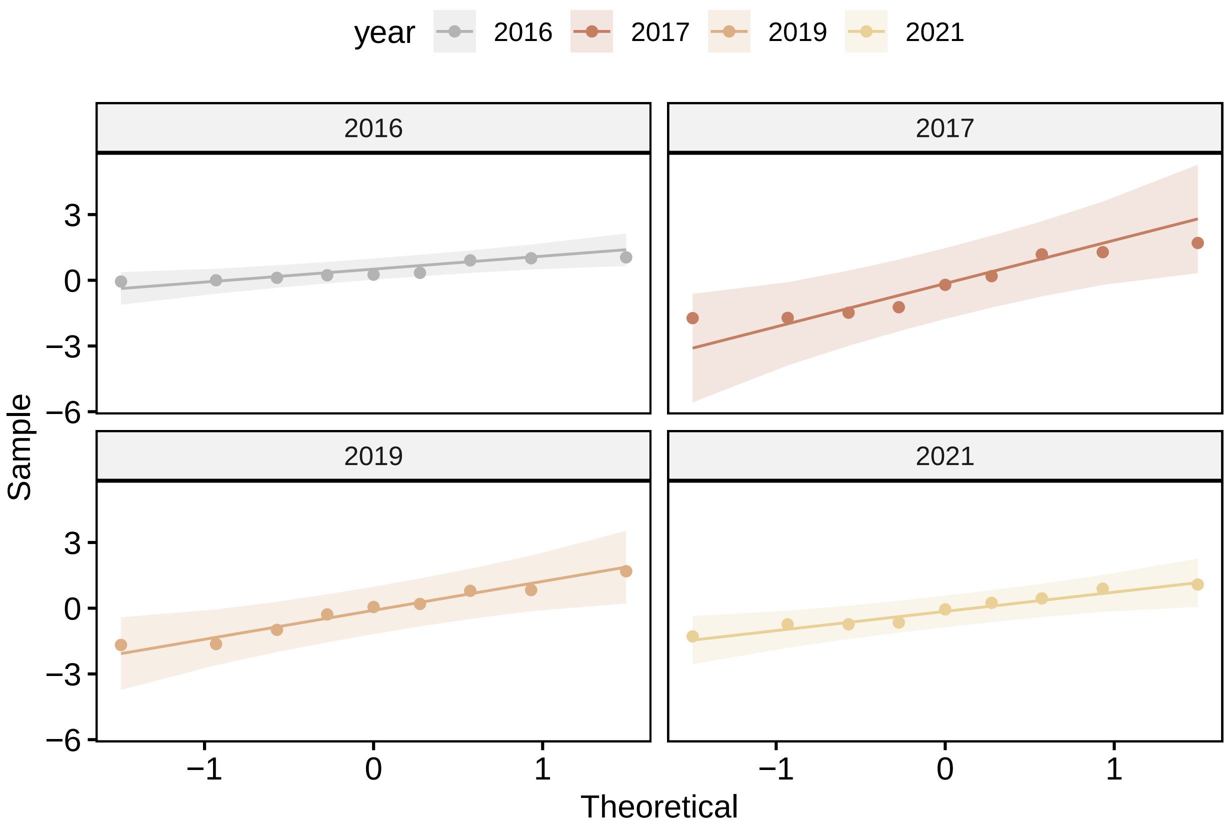


Normalize data and repeat checks We applied an arcsine transformation to normalize the plot-level values for total downed woody debris, calculated as log(x + sqrt(x^2 + 1)). The arcsine transformation (also called the arcsine square root transformation, or the angular transformation) was identified as 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 downed 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
Downed woody debris	All	2016	TRUE	0.0705051	0.848
Downed woody debris	All	2017	TRUE	0.1501308	0.878
Downed woody debris	All	2019	TRUE	0.6898519	0.950
Downed 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

Repeated measures ANOVA test

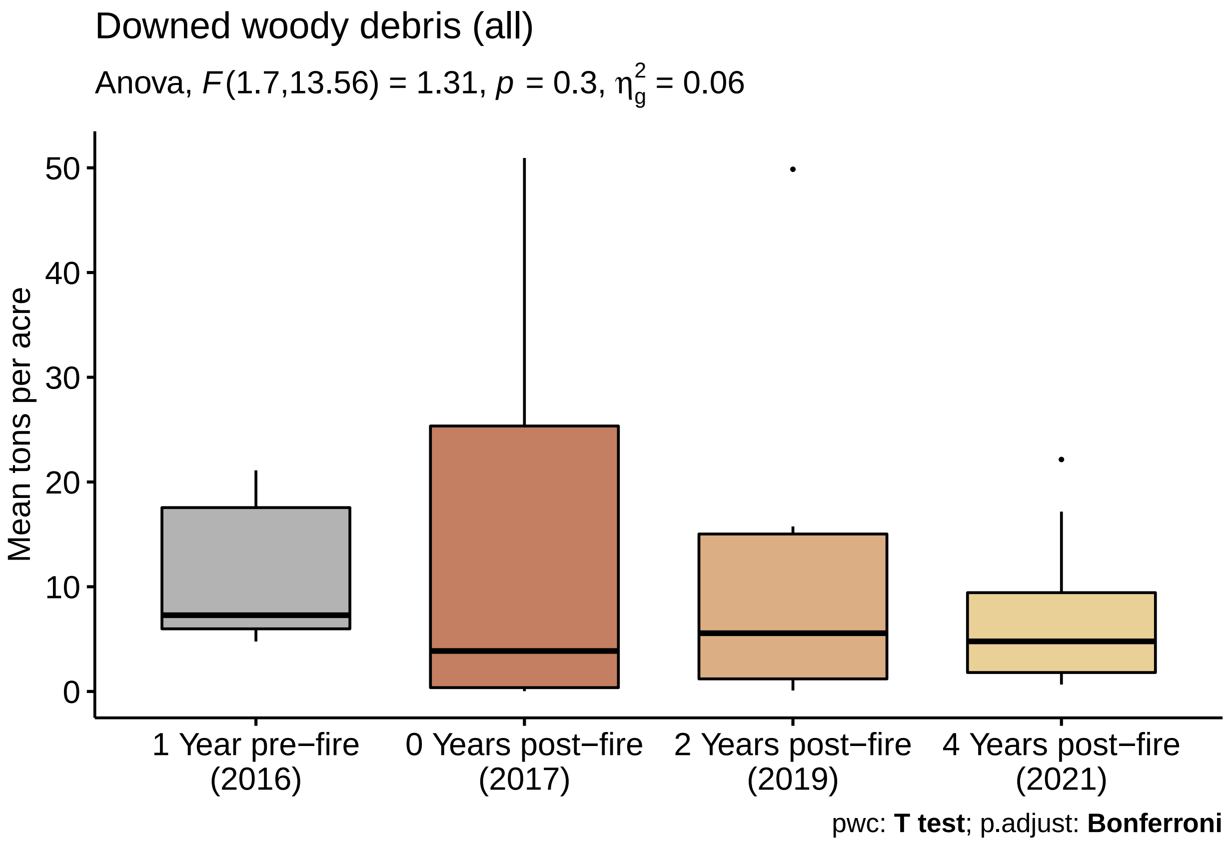
We found no significant main effect of year on the plot-level total for downed woody debris (p = 0.359).

data_type	fuel_class	effect	p_adj	p_adj_sig	statistic	d_fn	d_fd	ges	method
Downed 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 downed woody debris by year (the lack of p-values reflects the absence of significant comparisons), and (2) a table of test results.



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

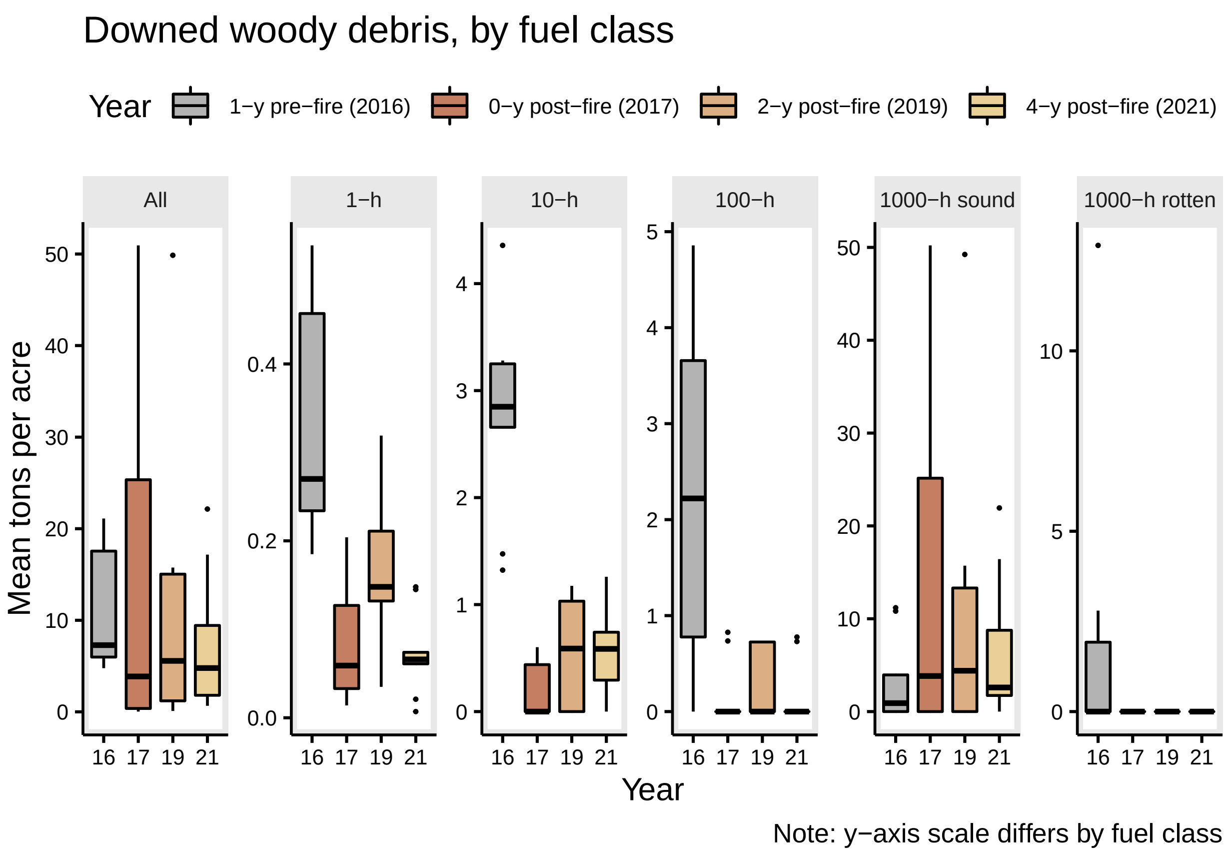
Summary statistics for downed woody debris by year and fuel class

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

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

Visualization of downed woody debris by year and fuel class

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



We observed a decrease in fuel load immediately after the fire (2017; 0-y post-fire) for all classes of downed 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 downed 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 downed 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.

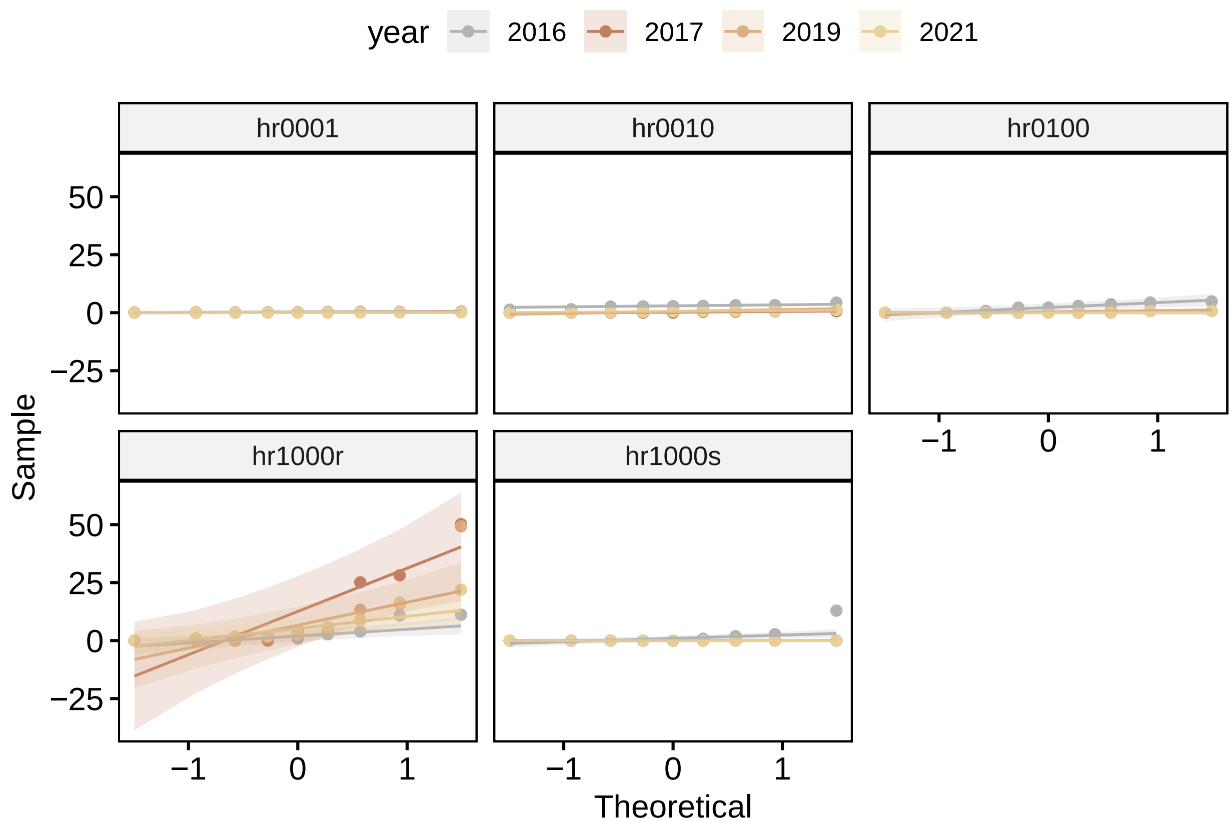
data_type	fuel_class	year	plot_id	value	is_outlier	is_extreme
Downed woody debris	hr1000s	2016	RxF04	12.924	TRUE	TRUE
Downed woody debris	hr0100	2017	RxF03	0.736	TRUE	TRUE
Downed woody debris	hr0100	2017	RxF08	0.826	TRUE	TRUE
Downed woody debris	hr0001	2021	RxF03	0.007	TRUE	TRUE
Downed woody debris	hr0001	2021	RxF04	0.145	TRUE	TRUE
Downed woody debris	hr0001	2021	RxF05	0.148	TRUE	TRUE
Downed woody debris	hr0001	2021	RxF08	0.021	TRUE	TRUE
Downed woody debris	hr0100	2021	RxF04	0.730	TRUE	TRUE
Downed 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
Downed woody debris	hr0010	2017	FALSE	0.0059166	0.753
Downed woody debris	hr0100	2017	FALSE	0.0000258	0.551
Downed woody debris	hr0100	2019	FALSE	0.0001664	0.620
Downed woody debris	hr0100	2021	FALSE	0.0000215	0.545
Downed woody debris	hr1000r	2016	FALSE	0.0036207	0.735
Downed woody debris	hr1000r	2017	FALSE	0.0066142	0.757
Downed woody debris	hr1000r	2019	FALSE	0.0008514	0.681
Downed 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.



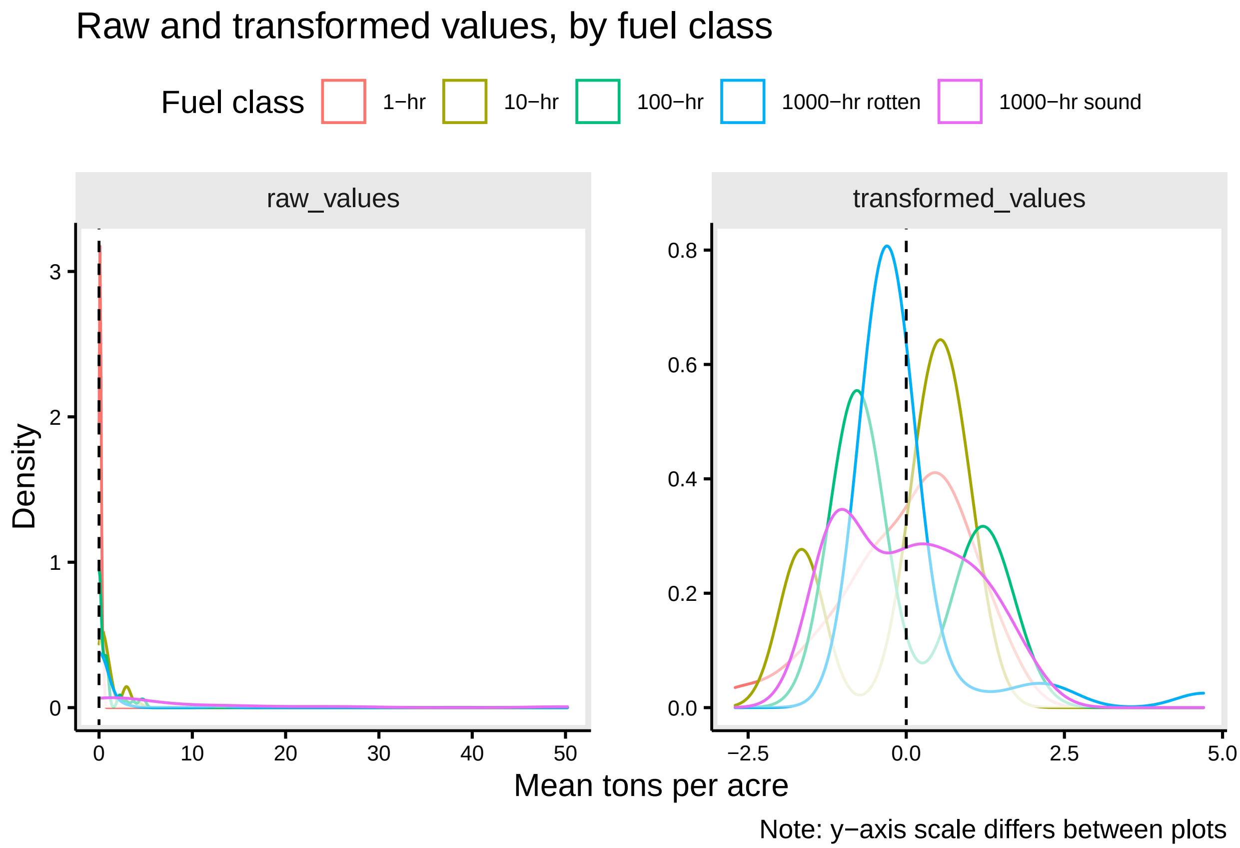
Normalize data and repeat checks We subset the plot-level values for downed woody debris by fuel class, then used the R function bestNormalize() [bestNormalize package] to identify and apply the best transformation for each subset. To normalize the plot-level values for the 1-hr, 10-hr, and 100-hr fuel classes we applied a log transformation, calculated as log(x). To normalize the plot-level values for the 1000-hr rotten and 1000-hr sound fuel classes we applied an arcsine transformation, calculated as log(x + sqrt(x^2 + 1)). 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.
```

fuel_class	transformation	mean_transformed	sd_transformed	mean_raw	sd_raw
1-hr	log	0	1	0.162	0.135
10-hr	log	0	1	1.016	1.171
100-hr	log	0	1	0.731	1.310
1000-hr rotten	arcsine	0	1	0.513	2.202
1000-hr sound	arcsine	0	1	8.103	12.719

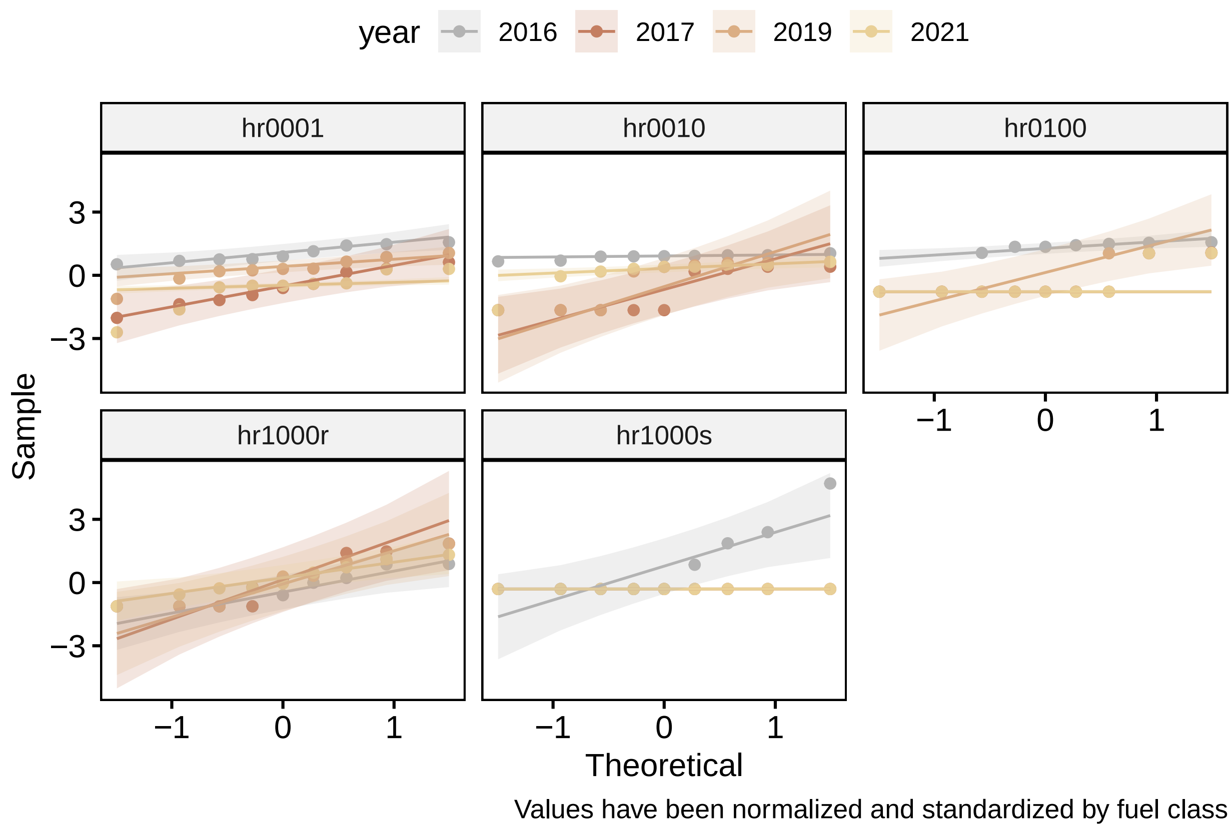
The following plot shows the raw (untransformed) values on the left and the transformed values on the right.



The transformed values for downed woody debris were normally distributed for more of the fuel class x year combinations; but still had 6 that were not normally distributed, as assessed by Shapiro-Wilk's test.

data_type	fuel_class	year	is_normal	p	statistic
Downed woody debris	hr0001	2021	FALSE	0.0463586	0.831
Downed woody debris	hr0010	2017	FALSE	0.0009239	0.684
Downed woody debris	hr0010	2019	FALSE	0.0014195	0.700
Downed woody debris	hr0010	2021	FALSE	0.0003706	0.650
Downed woody debris	hr0100	2016	FALSE	0.0004354	0.656
Downed woody debris	hr0100	2017	FALSE	0.0000181	0.538
Downed woody debris	hr0100	2019	FALSE	0.0001546	0.618
Downed woody debris	hr0100	2021	FALSE	0.0000175	0.537
Downed woody debris	hr1000r	2016	FALSE	0.0347403	0.820
Downed woody debris	hr1000r	2017	FALSE	0.0376696	0.823

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



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

Repeated measures ANOVA test

There was a statistically significant two-way interaction between downed woody debris class and year, F(12, 96) = 3.092, p-adj. = 0.002970, ges = 0.155. 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
Downed woody debris	year	0.000117	***	12.553	3	24	0.196	aov2
Downed woody debris	fuel_class:year	0.002970	**	3.092	12	96	0.155	aov2
Downed woody debris	fuel_class	1.000000	n.s.	0.000	4	32	0.000	aov2

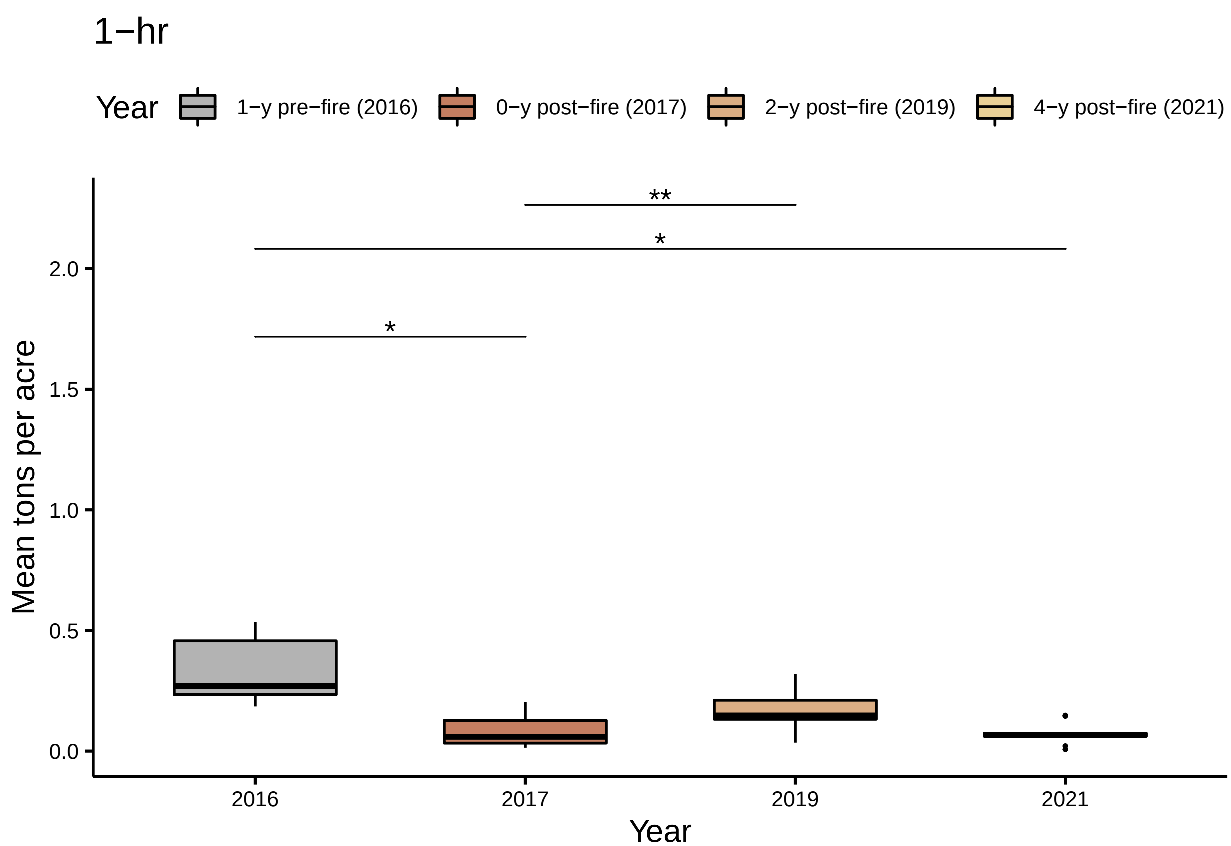
Post hoc tests

We found a significant main effect of year on fuel load for 1-hr ($p < 0.001$) and 10-hr ($p < 0.01$) fuel classes. No significant effect of year on fuel load was found for the 100-hr, 1000-hr rotten, or 1000-hr sound classes. One thing the pairwise comparison by fuel class had in common: For the two classes with a significant main effect of year on fuel load (1-hr, 10-hr), 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
Downed woody debris	hr0001	year	0.0001465	***	13.063	3.00	24.0	0.499	me
Downed woody debris	hr0010	year	0.0050000	**	7.262	3.00	24.0	0.372	me
Downed woody debris	hr0100	year	0.0700000	n.s.	4.319	3.00	24.0	0.294	me
Downed woody debris	hr1000s	year	0.0700000	n.s.	4.343	3.00	24.0	0.289	me
Downed woody debris	hr1000r	year	1.0000000	n.s.	0.819	1.67	13.4	0.043	me

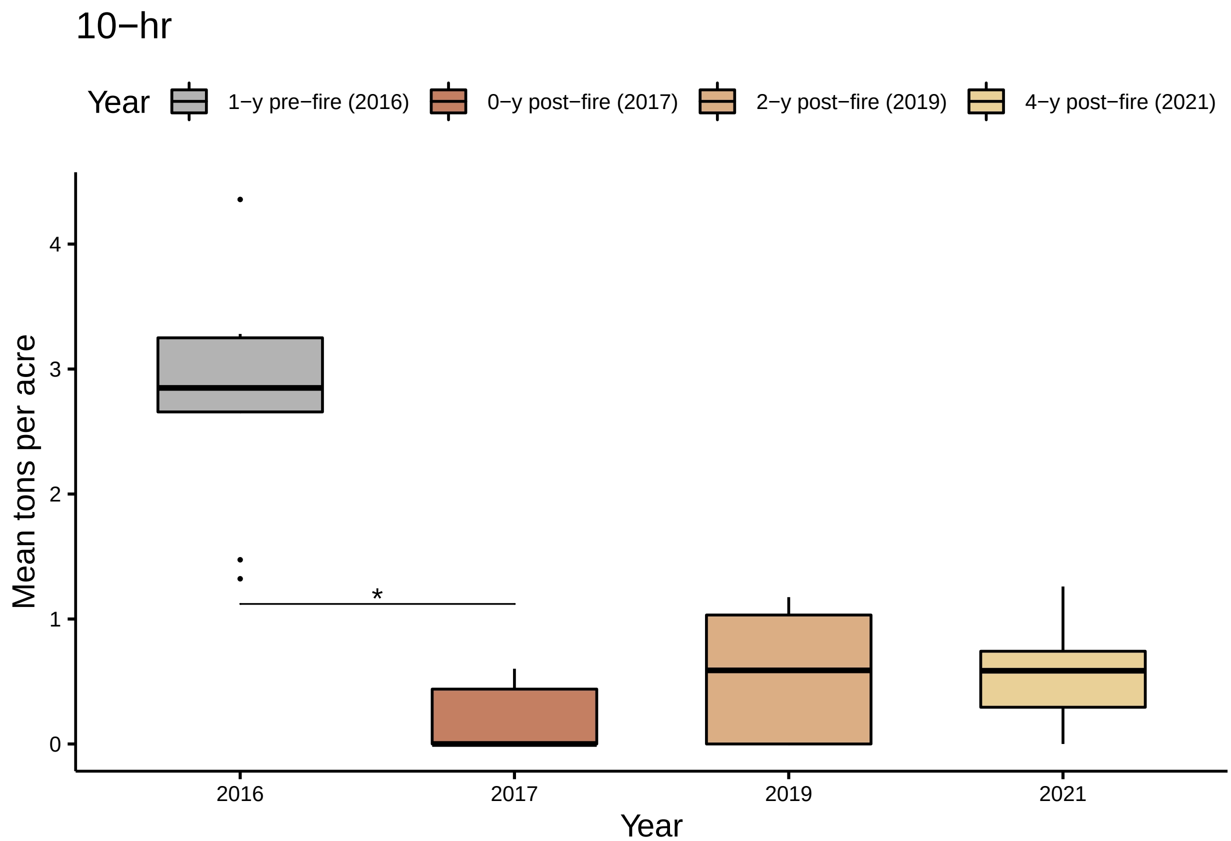
The following sections present the results from post hoc tests by fuel class for (1) the main effect of fuel class on fuel load at each time point, and (2) significant pairwise differences between years.

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



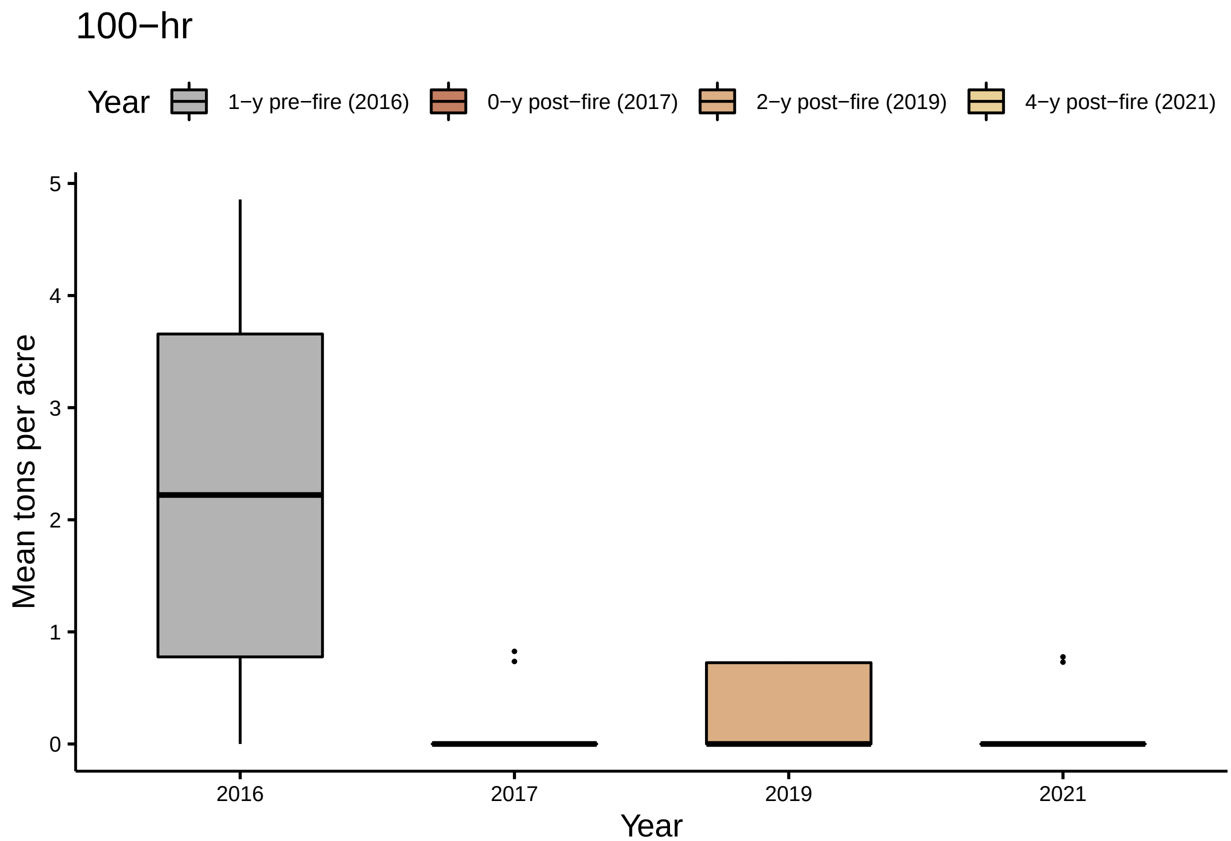
data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Downed woody debris	1-hr	2017	2019	0.003	**	-5.621	8	pwc
Downed woody debris	1-hr	2016	2021	0.010	*	4.627	8	pwc
Downed woody debris	1-hr	2016	2017	0.011	*	4.566	8	pwc
Downed woody debris	1-hr	2019	2021	0.076	ns	3.197	8	pwc
Downed woody debris	1-hr	2016	2019	0.196	ns	2.579	8	pwc
Downed woody debris	1-hr	2017	2021	1.000	ns	0.195	8	pwc

10-hour vs. Year A post hoc pairwise comparison showed a significant difference in 10-hr fuel load between 2016 and 2017 ($p < 0.05$). No other comparisons were significant.



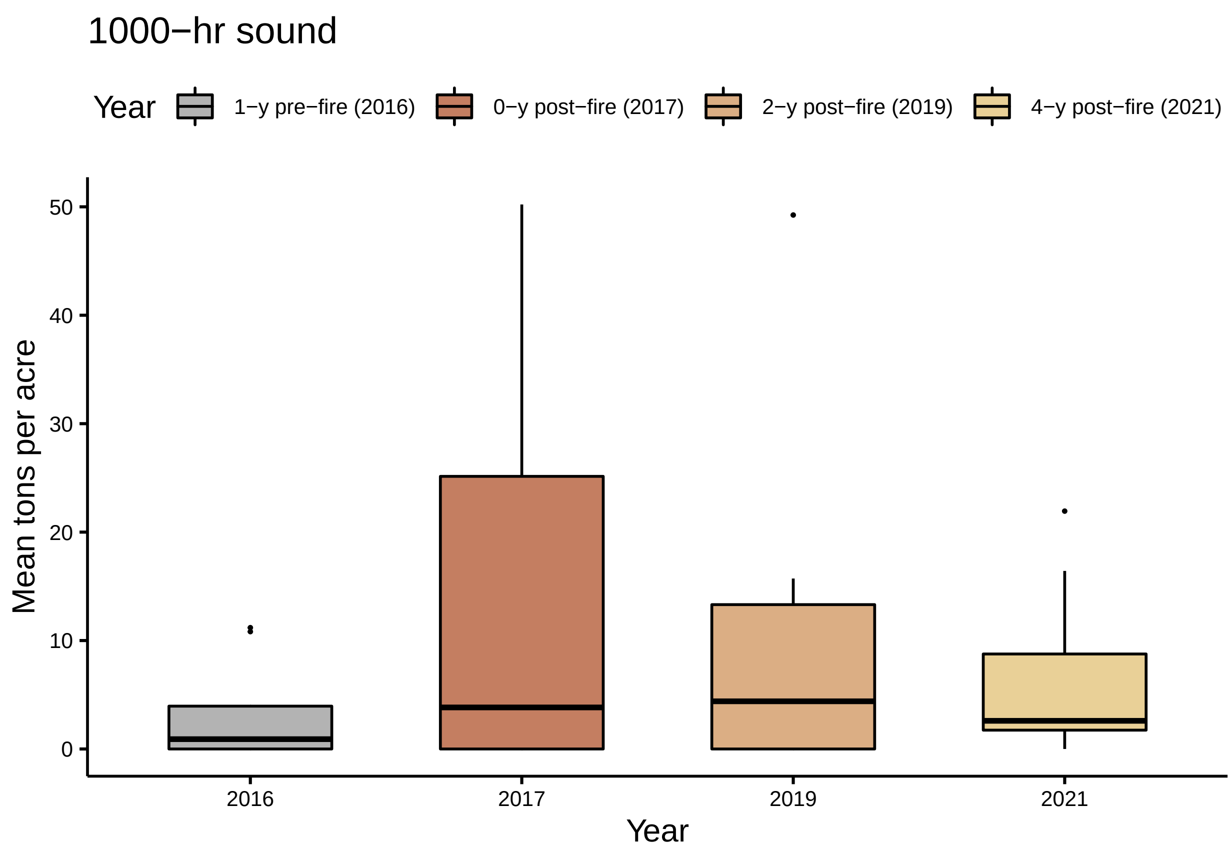
data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Downed woody debris	10-hr	2016	2017	0.013	*	4.460	8	pwc
Downed woody debris	10-hr	2016	2021	0.093	ns	3.063	8	pwc
Downed woody debris	10-hr	2016	2019	0.110	ns	2.951	8	pwc
Downed woody debris	10-hr	2017	2021	0.175	ns	-2.652	8	pwc
Downed woody debris	10-hr	2017	2019	0.744	ns	-1.716	8	pwc
Downed woody debris	10-hr	2019	2021	1.000	ns	-0.748	8	pwc

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



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Downed woody debris	100-hr	2016	2021	0.057	ns	3.391	8	pwc
Downed woody debris	100-hr	2016	2017	0.169	ns	2.676	8	pwc
Downed woody debris	100-hr	2016	2019	0.309	ns	2.287	8	pwc
Downed woody debris	100-hr	2017	2019	1.000	ns	-0.540	8	pwc
Downed woody debris	100-hr	2017	2021	1.000	ns	0.005	8	pwc
Downed woody debris	100-hr	2019	2021	1.000	ns	0.548	8	pwc

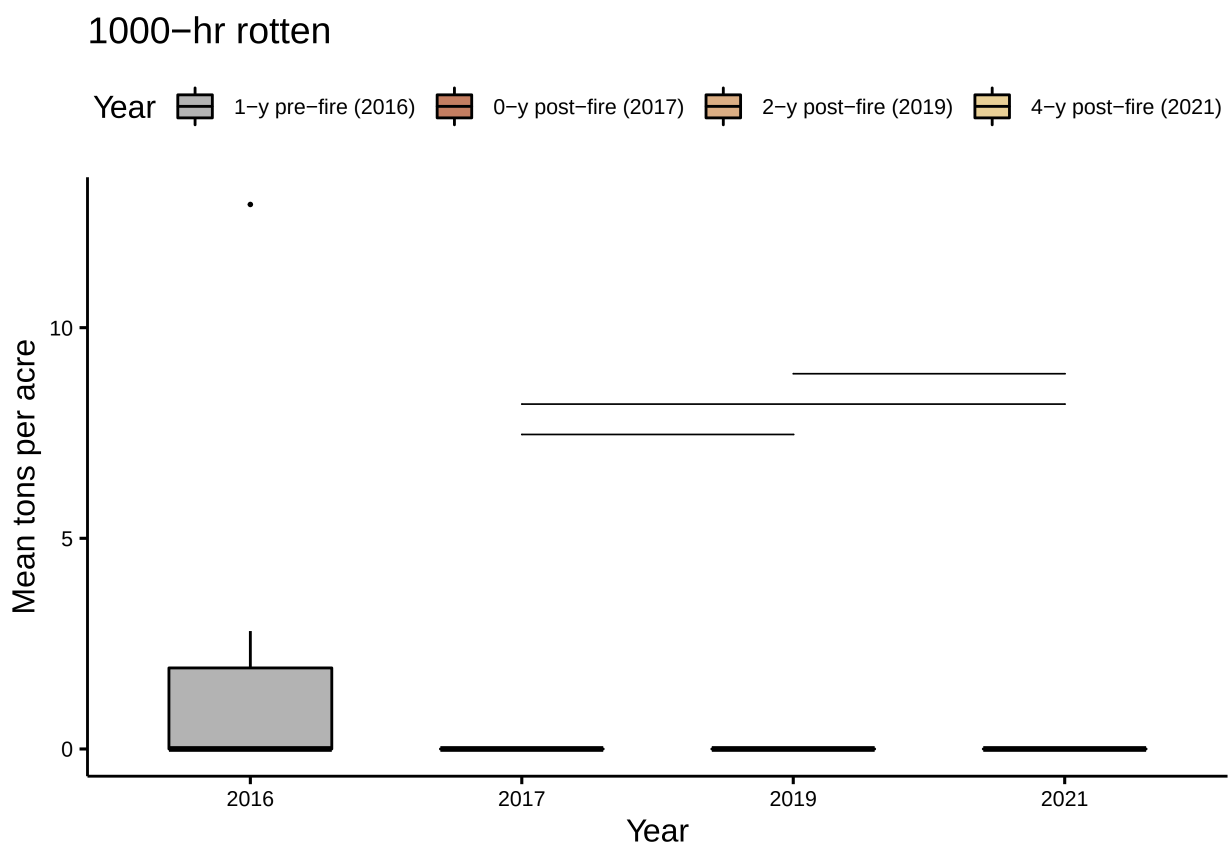
1000-hour rotten vs. Year Post hoc comparisons showed no significant difference in 1000-hr rotten fuel load between years at a significance level of <0.05.



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Downed woody debris	1000-hr sound	2016	2017	1	ns	-0.917	8	pwc
Downed woody debris	1000-hr sound	2016	2019	1	ns	-0.991	8	pwc
Downed woody debris	1000-hr sound	2016	2021	1	ns	-1.366	8	pwc
Downed woody debris	1000-hr sound	2017	2019	1	ns	-0.099	8	pwc
Downed woody debris	1000-hr sound	2017	2021	1	ns	-0.163	8	pwc
Downed woody debris	1000-hr sound	2019	2021	1	ns	-0.155	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.



data_type	fuel_class	group1	group2	p_adj	p_adj_sig	statistic	df	method
Downed woody debris	1000-hr rotten	2016	2017	0.212	ns	2.084	8	pwc
Downed woody debris	1000-hr rotten	2016	2019	0.212	ns	2.084	8	pwc
Downed woody debris	1000-hr rotten	2016	2021	0.212	ns	2.084	8	pwc
Downed woody debris	1000-hr rotten	2017	2019	NaN		NaN	8	pwc
Downed woody debris	1000-hr rotten	2017	2021	NaN		NaN	8	pwc
Downed woody debris	1000-hr rotten	2019	2021	NaN		NaN	8	pwc

Date of last revision
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