Factors affecting natural regeneration of woody vegetation following severe fire in *Pinus nigra* forests: a year zero assessment

MSc Forest Science

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Contents

Abstract

Pinus nigra (black pine) is an ecologically important species in the Mediterranean Basin. Black pine plantations were established in the early 20th century to prevent soil erosion in mountain environments around Italy. The unmanaged pine stands tend to develop an understory of broadleaves, including *Quercus ilex*, *Ostrya carpinifolia*, *Fraxinus ornus*, *Acer spp.*, and *Quercus spp.* As fire increases in frequency and severity in the Mediterranean Basin, these already endangered habitats are increasingly at risk. This study aims to investigate the role of biological legacies and topographic factors that affect the natural regrowth of woody vegetation following severe fire in montane *Pinus nigra* forests. *Pinus nigra* lacks fire-specific adaptations such as serotiny, resprouting, or a seed bank. This year-zero study of regeneration of woody vegetation will help highlight what topographic factors and material legacies best support regrowth immediately after fire and provides insight into the future makeup of the post-disturbance community. Legacies and topography that regulate temperature extremes, soil moisture, and soil temperature created microsites that were conducive to increased regeneration density and greater performance of woody regeneration. Regenerative strategies—obligate reseeding, obligate resprouting, and facultative seeding—were analysed to determine which strategy was most successful in specific microclimatic conditions immediately after severe fire.

Introduction

The abandonment of cropland and afforestation of montane areas left large areas of unmanaged black pine (*Pinus nigra* J.F. Arnold) forests in the Mediterranean Basin (Gil-Tena et al., 2016;Mercurio & Schirone, 2015) Black pine was planted to prevent soil erosion in mountain environments around Italy in the early 20th century (Mercurio & Schirone, 2015). These now unmanaged pine stands are developing an understory of broadleaves, including *Quercus ilex* L., *Ostrya carpinifolia* Scop., *Fraxinus ornus* L., *Acer spp.*, and *Quercus spp.* (Mercurio & Schirone, 2015). As these areas become more prone to fire (Oliveira et al., 2018), the landscape will be subject to change.

Black pine is considered mildly fire tolerant (Christopoulou et al., 2014) due to its relatively thick bark, but is vulnerable to high-severity fire due to its non-serotinous cones, lack of a canopy seed bank, and the timing of seed dispersal in the early spring just before fire season (Christopoulou et al., 2014; Gracia et al., 2002; Martín-Alcón & Coll, 2016; José Luis Ordóñez et al., 2006). The natural regeneration of plant species, including trees, following a disturbance can be facilitated by disturbance legacies. In general, there are two types of legacies following disturbance, material and informational legacies (Johnstone et al., 2016). The former are physical materials present after disturbances—fallen logs, snags, surviving vegetation, seeds, or other matter depending on the ecosystem and the characteristics of disturbance; the latter are species history traits such as serotiny, clonal propagation, or other adaptations to disturbance frequencies and types. The combination of these two legacies form ecological memory (Johnstone et al., 2016). The material legacies following fire in artificial black pine stands are snags and deadwood, any surviving vegetation—unlikely after severe fire—and abiotic, non-flammable material such as rocks or mineral soil. Black pine does not generally have a seed bank following severe fire, as its cones are non-serotinous and disperse in early spring, just prior to fire season (Ordóñez et al., 2005; Ordóñez et al., 2006). The informational legacies in this case are the fire-adapted resprouting species of the understory. Common species found post-fire include resprouting oaks (Baudena et al., 2020; Martín-Alcón & Coll, 2016; Retana et al., 2002) and shrub species in the genus *Rubus*, *Crataegus*, and *Viburnum* (Martín-Alcón & Coll, 2016; Retana et al., 2002).

Microsites—created by material legacies and microtopographic elements—that can support woody regeneration can be determined by factors such as topography (Lucas-Borja et al., 2011; Martín-Alcón & Coll, 2016; José Luis Ordóñez et al., 2006), soil moisture (Christopoulou et al., 2014; Ordónez et al., 2004), and the facilitating effect of shrubs and other forms of land cover such as coarse woody debris (Christopoulou et al., 2014; Gracia et al., 2002; Martín-Alcón & Coll, 2016; Ordónez et al., 2004). Black pine may perform best in mesic microhabitats (Gracia et al., 2002; Lucas-Borja et al., 2011) and under some degree of canopy or vegetative cover (Christopoulou et al., 2014; Gracia et al., 2002; Ordónez et al., 2004). These conditions may arise through material legacies after fire. Coarse woody debris, for example, can provide higher water content than adjacent soils, reduce inter-species competition, and provide physical cover (Johnson & Alan Yeakley, 2016). Vegetative cover can provide the necessary shade for black pine recruitment, reduce heat stress, lower temperature variation, and facilitate higher soil moisture (Christopoulou et al., 2014; Ordónez et al., 2004).

Forest succession assumes a disturbed site will likely return to the same pre-disturbance climax community—a pathway called *autosuccession*—in the event that the dominant tree or woody vegetation in the overstory has a viable reproductive strategy post fire (Arnan et al., 2007; Walker et al., 2013). Fire severity can be an explanatory variable with respect to regeneration patterns (Vasques et al., 2023). There are several common adaptations to fire in this region: obligate seeding, in which plants regenerate exclusively from a surviving seed bank; obligate resprouting, in which plants mainly regenerate after fire from still-living stumps or roots until they reach maturity and begin producing seeds in the absence of disturbance; and facultative seeding, in which the two previous strategies are combined immediately after fire (Vasques et al., 2023). High severity and frequent recurrence of fire can reduce the success of obligate resprouters, such as oaks, resulting in a "delayed" successional pathway that favours the regrowth of facultative seeder species (Vasques et al., 2023), although Marais et al. (2014) found that fire severity was not a reliable predictor of success of obligate resprouting species versus facultative regeneration.

In the case of *Pinus nigra*, these stands have no reproductive strategy to ensure autosuccession in the case of severe fire (Arnan et al., 2007; Martín-Alcón & Coll, 2016; Ordónez et al., 2004; Jose Luis Ordóñez et al., 2005). However, obligate resprouters and facultative seeders that establish earlier have been found to have better survivorship postfire (Marais et al., 2014), suggesting the early successional community will be established relatively quickly post fire. Mediterranean pine forests are predicted to transition to open oak and shrub forests following fire (Gracia et al., 2002; Martín-Alcón & Coll, 2016; Retana et al., 2002), particularly as the climate warms and more arid conditions prevail (Baudena et al., 2020). Black pine forests in particular tend to transition to open shrubland after high mortality following fire (Retana et al., 2002). One study found that the conversion to open shrubland or oak-dominated forest depends on land use prior to fire, with recently abandoned cropland changing mainly to shrub-dominated and long-abandoned cropland transitioning to oak-dominated forests after fire in black pine forests (Retana et al., 2002). With respect to woody vegetation, facultative seeders appear to have an early competitive advantage by combining both resprouting and regenerating from a seed bank (Keeley et al., 2006; Vasques et al., 2023).

The burnt areas in this study originated from two large wildfires that began in late July, 2022, and quickly became some of the largest wildfires in Slovenia's history (Korosec, 2022). The fires affected the eastern part of Friuli Venezia Guilia (proper Venezia Giulia, or Carso) region in Italy and the Karst area in Slovenia (Figure 1). The fire resulted from the combination of drought in these regions, along with a heat dome that resulted in a prolonged period with temperatures at or near 40° Celsius. Over 3,500 hectares burned in the first few days of the fire, sparking a multinational firefighting response (Korosec, 2022). The fire of interest started on the 17th of July in Slovenia between Rence and Kostanjevica na Krasu and was followed by another fire that began in Italy on July 19th and started between Gorizia and Trieste.

This region features the Karst Plateau, which extends across the border from southwestern Slovenia to northeastern Italy. The Carso region is largely dominated by pine plantations, largely consisting of black pine (Stančič & Repe, 2018). The plateau has a steep

western ridge known as the Karst Rim, thus cutting it off from the more mild, humid climate of the Adriatic. Karst is the German word for stone, and this plateau is characterized by the soft carbonate stone (Figure 2) that often forms depressions and expansive cave systems (Hajna, 2003). Due to its highly permeable bedrock, high cover of pine plantations (*P. nigra* and *P. sylvestris*), and proximity to anthropogenic settlement and rail lines, this region is at a high risk for wildfire Drought conditions are frequent despite high precipitation levels due to a lack of retention in the carbonate bedrock. (Hajna, 2003; Stančič & Repe, 2018).
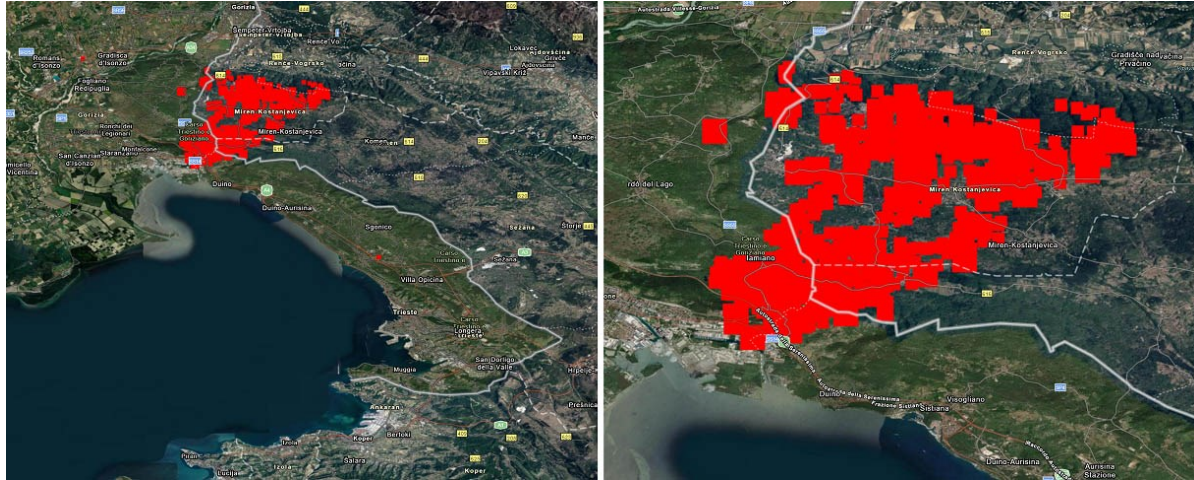

Figure 1: Extent of the Carso Fire Complex, retrieved from severe-weather.eu.

In this study, there were ninety-seven sample plots surveyed for woody vegetation regeneration nine months after the Carso fire, to determine the level and composition of regeneration in the first year after fire. Few studies have been conducted on the post-fire recovery in the Carso region, particularly on the year-zero dynamics. One study compared the 11 month regeneration following a surface fire in the region to an older burn and unaffected areas (Stančič & Repe, 2018). Though they found that succession occurs rapidly, the shrub and field layers in the more recent site were significantly more sparse and less diverse, dominated by *Fraxinus ornus*, *Quercus petraea*, and *Juniperus communis*, as well as *Prunus spinosa*. As many Mediterranean shrub species prefer warm, dry, sunny areas, they also act as pioneer species and recolonize quickly following fire (Stančič & Repe, 2018).
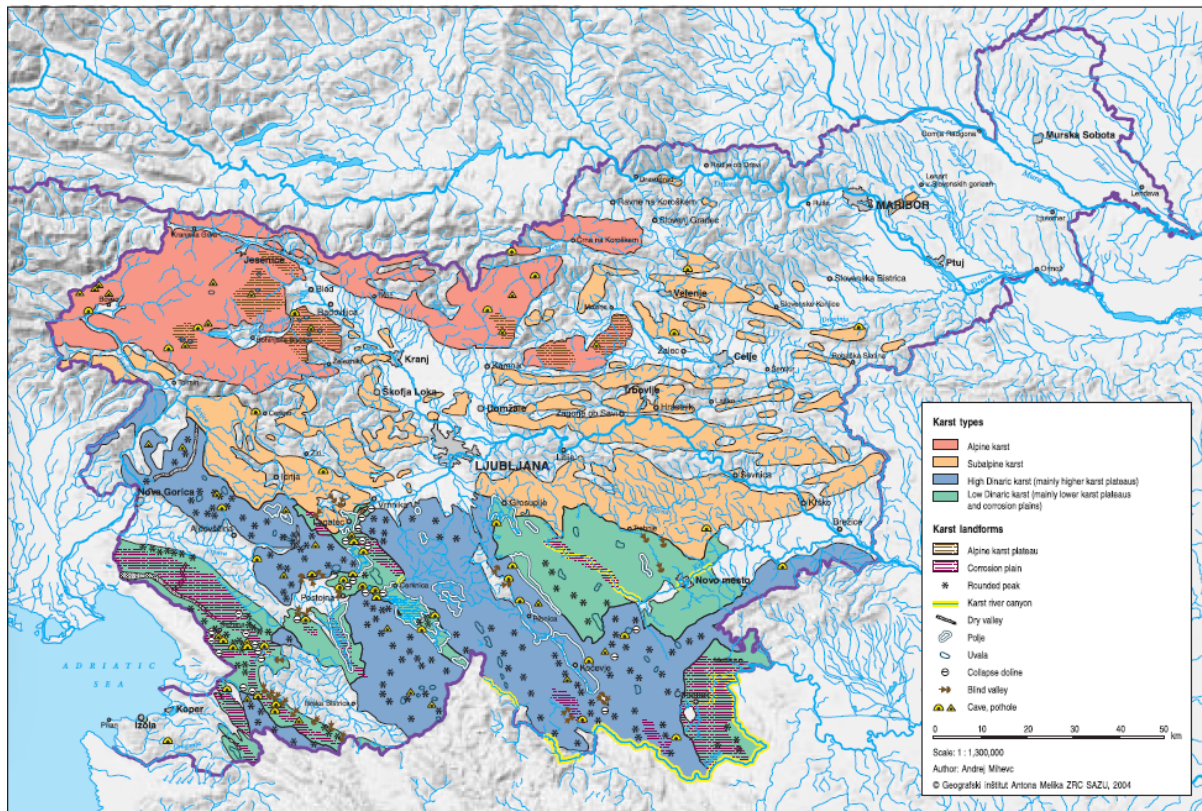
Figure 2: Geological Map of Carso/Karst Plateau. Retrieved from Hajna, 2003.

Problem

Abandoned black pine plantations on the Karst Plateau are increasingly prone to severe wildfires (Oliveira et al., 2018). While studies have shown that these stands generally transition to open oak-shrub forests (Gracia et al., 2002; Martín-Alcón & Coll, 2016; Retana et al., 2002), there are relatively few studies on the immediate response post-fire (Stančič & Repe, 2018), especially with respect to material legacies left after disturbance. As black pine is poorly adapted to severe fire, these landscapes will change quickly, and the success of early successional and fire-adapted species may help reveal the future climax community.

Hypotheses

Early woody vegetation regeneration will be fostered by material legacies and topographic conditions that regulate temperature and soil moisture – coarse woody debris cover, understory cover, and rock/stone cover.

Woody regeneration density and performance will be dominated by facultative seeders, as the use of both regeneration strategies—resprouting and seeding—will allow for the colonisation of beneficial microsites.

Objectives

This study investigates regeneration following severe (crown) fire, aiming to determine the relationship of various material legacies and topographic factors on the density and performance of regeneration within the first year following fire. Analysis of performance of regeneration strategies will aid in the prediction of successional pathways after severe fire in black pine stands.

Materials and Methods

Surveying and Study Plot Measurements

Patches of severe fire from the August 2022 fire along the Italian-Slovenian border were selected for sampling based on size, severity, and proximity to anthropogenic structures such as roads. Within these patches, ninety-seven circular sample plots with a 6m radius were surveyed (Figure 3). There were ninety-six high severity sites sampled, and one site was considered medium severity upon a revisit. The study area was part of the August 2022 Carso fire complex,
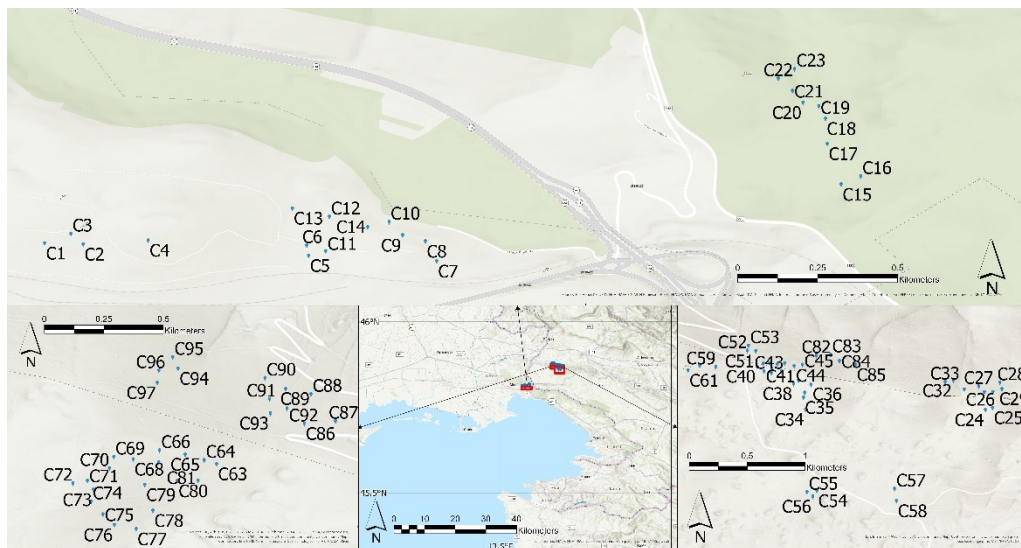
Figure 3: Sample Plots C1-C97 in Friuli Venezia Guilia (left) and Karst (right) regions.

which had burned over two weeks in August of the year prior to sampling. This survey allowed for the recording and analysis of regrowth within the first year following severe fire. Characteristics measured include the height, type (gamic/agamic), number of stems—in the case of agamic regeneration, and species of all regenerating woody vegetation. Material legacies were described through % estimations of groundcover—soil cover, rock cover, and non-woody vegetation cover; the latter was split into phanerophytes, chamaephytes, monocotyledons, and

dicotyledons—as well as estimates of coarse woody debris, including snags. The average length and modal diameter of coarse woody debris were recorded, along with the number of pieces, to allow for estimation of volume during statistical analysis. Site characteristics such as elevation, slope, and aspect were derived from digital terrain models (next section). Site locations were recorded using an EMILD Reach RS2—a precision GNSS unit.

Remote Sensing

The topographic data were derived from two digital elevation models: one from the National Geoportal of Italy, which covered the Italian side of the border just north of Trieste, and the other from the Ministry of the Environment and Spatial Planning, Slovenian Environment Agency, which covered the rest of the sample plots on the Slovenian side of the Italian-Slovenian border. The sample plot centre points were imported into ArcGIS using recorded latitude and longitude from the precision GNSS unit. The geoprocessing toolbox allowed for the calculation of slope, aspect, and elevation directly from the digital terrain model. The Sample tool was used to collect the average value of slope, elevation, and aspect from underneath the study plots. These attributes were joined to the study plots shape layer. The attribute table was exported to a CSV file to later be imported into R for manipulation and analysis.

Data Processing and Preparation

Regeneration was reported in two ways: average height of regeneration at each site (performance) and the number of stems per hectare (ha) at each site (density). An attempt to find allometric equations to determine the volume (biomass) of regeneration was also carried out. There is a significant body of work in this area, including specific Mediterranean-native shrubs (Muukkonen, 2007; Usó et al., 1997), but they need dry masses or measures of diameter which were not collected due to the exceedingly small size of the regeneration being surveyed. The regeneration response was also split by post-fire regeneration strategy (see Table 1). The performance and density of regeneration for obligate resprouters, obligate seeders, and facultative seeders was derived from the species count and height at each plot. Species were sorted according to the USDA's Fire Effects Information System Index of Species Information (USDA, n.d.). Where species-specific information could not be found, they were matched by genus.

Following the retrieval of topographic data from ArcGIS, the survey and topographic data were imported into R for preparation and analysis. The data entry software did not record sites with zero counts of regeneration, as no data were recorded for theses sites. The first step was to account for these "zero-value" sites. The plot-specific topographic data and stem counts were added to a data frame. From the total stem count, an average stem count per hectare was calculated by dividing the total number of stems by the plot size ($113.1m^2$), and multiplied by $10,000m^2$ to retrieve an average stem density for each sample plot. A separate data frame was compiled with the stem height for each species sampled in each plot. From this data frame, an average stem height for each plot was calculated and added to the plot data frame as the performance measure. These two response variables were initially broken down further to analyse the performance and density of conifers and broadleaves, but the between-plot homogeneity of regeneration prevented meaningful analysis of these groups.

Table 1: Study species listed by regeneration strategy.

Regeneration Strategy	Species
Obligate Seeders	*Ailanthus altissima* (Mill.) Swingle
	Pinus halepensis Mill.
	Pinus nigra J.F. Arnold
Obligate Resprouters	*Quercus pubescens* Willd.
	Quercus ilex L.
	Pistacia lentiscus L.
	Ostrya carpinifolia Scop.
	Fraxinus ornus L.
Facultative Seeders	*Cotinus coggygria* Scop.
	Crataegus monogyna Jacq.
	Prunus mahaleb L.
	Ligustrum vulgare L.
	Rosa spp.
	Rhamnus alaternus L.
	Rhamnus cathartica L.
	Robinia pseudoacacia L.
	Amorpha fruiticosa L.

The independent variables were broken down into relevant classes to aid in data analysis and comprehension (See Figures 4-6). Aspect was reported in the ordinal directions; elevation was divided into four classes; and slope was divided into three classes (Figure 4). The vegetative ground cover variables, i.e., phanerophyte cover, chamephyte cover, dicotyledon cover, and monocotyledon cover, were combined into one "vegetative ground cover" class due to a high count of zero values and extremely low presence values owing to the short post-fire regeneration period. This vegetative ground cover class is reported as a presence or absence in each plot, applying a cover threshold (Figure 5). The non-living ground cover variables, i.e., mineral soil, rock, and leaf litter, were reported independently (Figure 6). All three cover types were classed into three respective categories. Deadwood volume was calculated using diameter and length of recorded snags and logs in each plot and categorized into four classes.

Statistical Analysis

Due to the short post-fire regeneration period, the response data were extremely right skewed (Figure 8), meaning there was exceptionally low stem density, and the average stem height was low. To transform the data to a more normal distribution for better analysis, a Tukey transformation ladder was applied (Lane, 2023). Tukey's transformation is defined as such (Eq. 1):

$$y = \begin{cases} x^\lambda & if\ \lambda > 0 \\ \log x & if\ \lambda = 0 \\ -(x^\lambda) & if\ \lambda < 0 \end{cases} \qquad (1)$$

The lambdas in Eq. 1 were respectively calculated for density and performance using the gld package in R. Regarding performance, $\lambda = 0.375$ was applied, and $\lambda = 0.35$ was applied to the density data (Figures 9 and 10). However, upon testing for normality following this transformation and with a Shapiro-Wilk test, the transformation was unable to ensure normal distribution. Thus, the data were left in their original distribution and non-parametric statistical tests were used in analysis.

Results

Grouping of Independent Variables

The independent variables were sorted into categorical classes to aid in data analysis and comprehension (Figures 4-6). Aspect was reported in the ordinal directions. Elevation was divided into four classes: Sea level (<100m), low (<408m) medium (<445m), and high(≥445m). These groups were determined by the bimodal elevation distribution, with a large gap between 100 and 250m. The low/medium/high classes were derived by splitting the higher of the two peaks into thirds. Slope was divided into three classes: flat (<10%), moderate (<20%) and steep (≥20%) (Figure 4).

The vegetative ground cover variables, i.e., phanerophyte cover, chamephyte cover, dicotyledon cover, and monocotyledon cover, were combined into one "vegetative ground cover" class due to a high count of zero values and extremely low presence values owing to the short regeneration period post-fire. The vegetative ground cover class was reported as a presence (cover ≥5%) or absence (cover < 5%) in each plot (Figure 5) These presence/absence classes were based on the 90th percentile of the vegetative cover class.
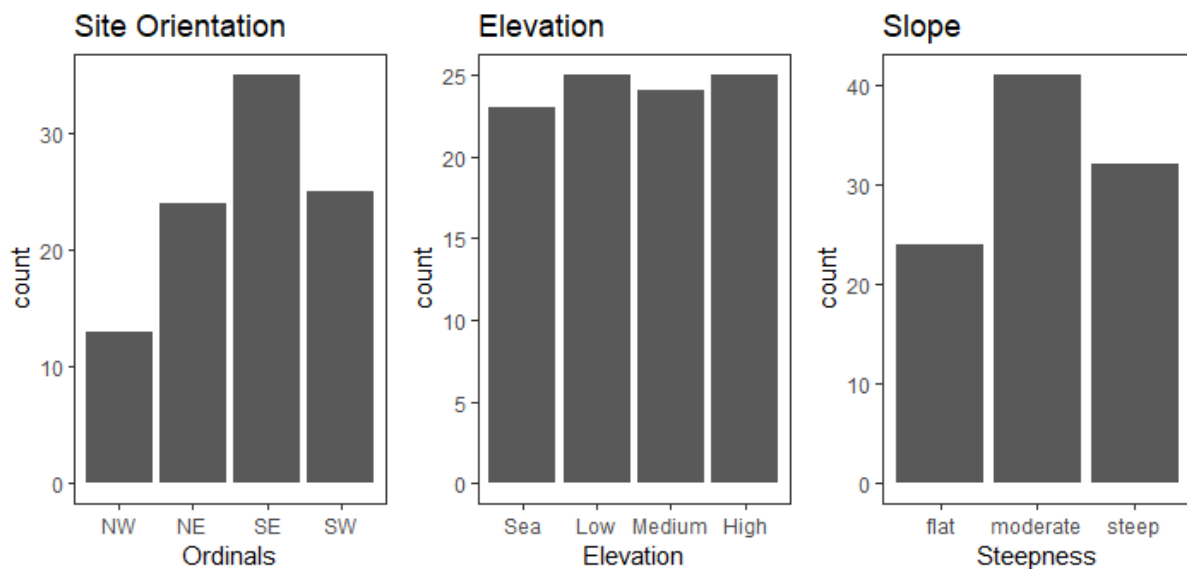
Figure 4: Topographic variable classes for aspect, elevation, and slope.
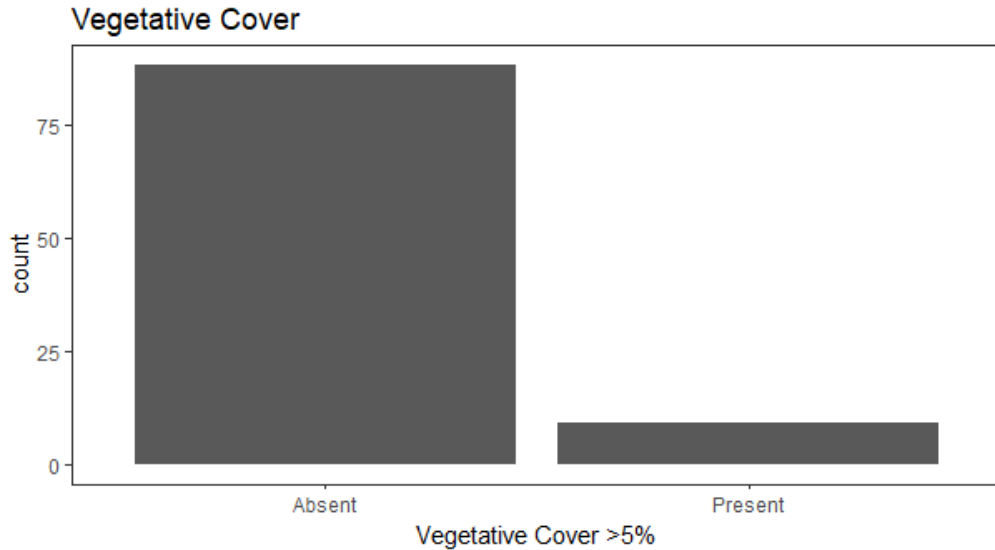
Figure 5: Site counts with vegetative cover over 5%.

The non-living ground cover variables, i.e., mineral soil, rock, and leaf litter, were reported independently (Figure 6). Mineral soil cover was classed into low (<35%), medium (<60%), and high (≥60%) classes. Rock cover was also classed into low (<35%), medium (<60%), and high (≥60%) classes. Leaf litter was classed into none (0%), low (<50%), and high (≥50%) classes. Deadwood (Figure 7) was sorted into three classes: Low (<2.3m^3), medium (<3.9m^3), and high (≥3.9m^3). These classes were derived by splitting the data according to 33%, 66%, and 100% percentiles.
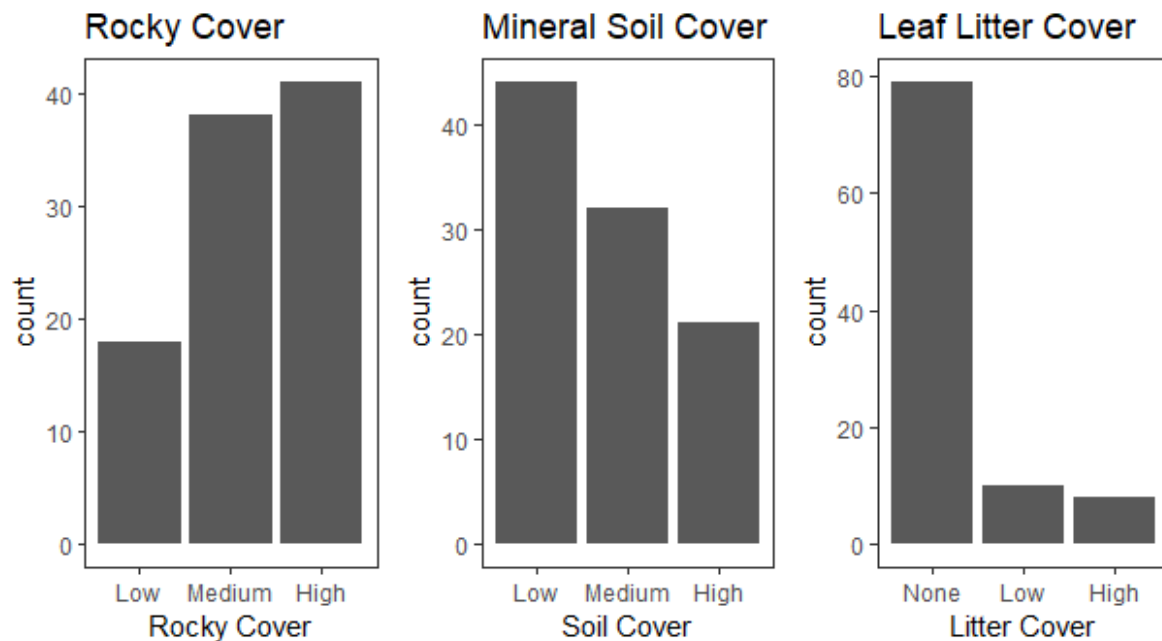
Figure 6: Non-living ground cover class distributions.
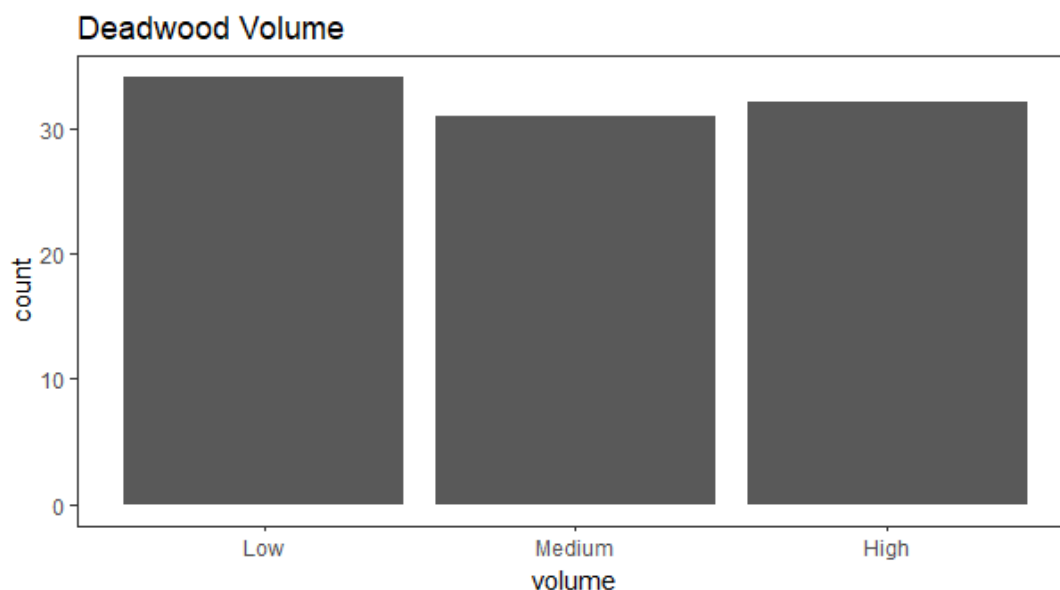
Deadwood Volume

Figure 7: Deadwood volume class distribution.

Regeneration Density and Performance

The Tukey transformation ladder applied to regeneration density (Figure 9) and regeneration performance (Figure 10) was intended to create a more normally distributed dataset
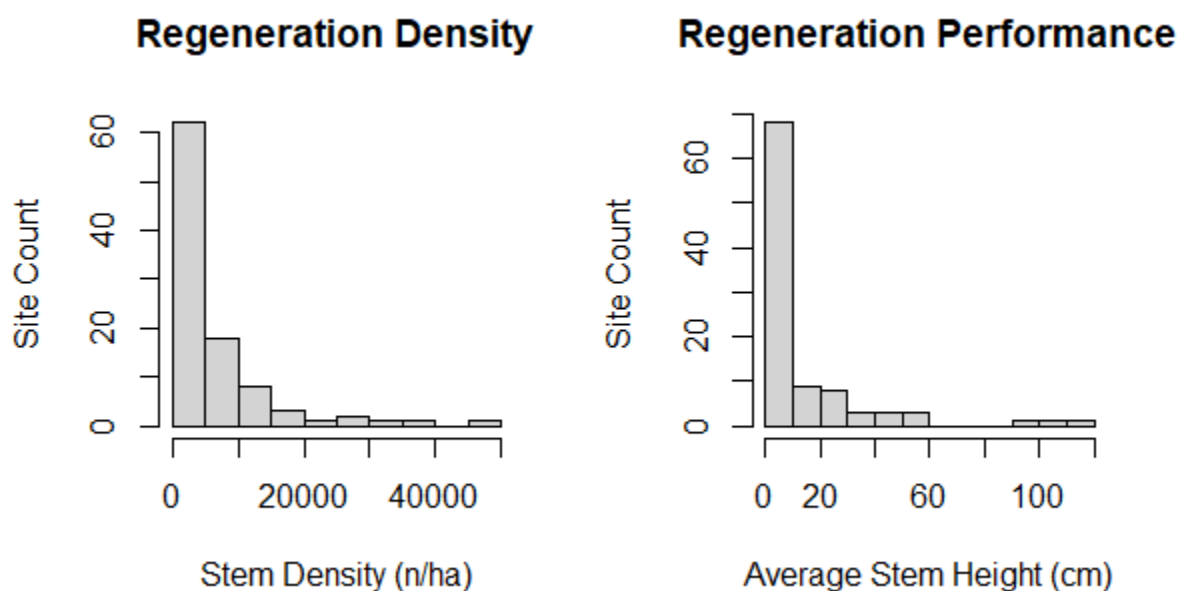
Figure 8: Woody regeneration density and performance histograms.

to allow for the application of ANOVA and Tukey tests. The transformed regeneration density appears to be more normally distributed than the transformed performance when comparing the Q-Q plots in Figures 8 and 9, however both response variables showed resistance to transformation with Shapiro-Wilk tests yielding p-values of <0.00006 for the regeneration performance distribution and <0.008 for the stem density distribution. The data were left in their

original distribution (Figure 8) and analysed with Kruskal-Wallis tests, followed by post-hoc Dunn tests if significance was determined. As shown in Table 2, not all topographic characteristics and legacies had an impact on woody regeneration density and/or performance. Of the topographic variables, slope and elevation showed difference in ranked means ($p<0.001$ in all cases) for both performance and density while the difference between ranked means of plot aspect was negligible ($p>0.1$ in both cases). In terms of material legacies, volume of deadwood influenced regeneration density ($p<0.05$), but not performance ($p>0.09$). Vegetative ground cover, leaf litter, and soil cover show significant effect ($p<0.05$ in all cases), indicating an effect on both performance and density of woody regeneration. The rocky cover class showed significance only with respect to the height of regeneration ($p<0.01$), but not with respect to density ($p>0.7$).

Figure 9: Attempted Tukey transformation ladder results on woody regeneration density. From left to right: Tested lambda values, transformed data histogram, and QQ plot comparing the transformed data to a Gaussian distribution.
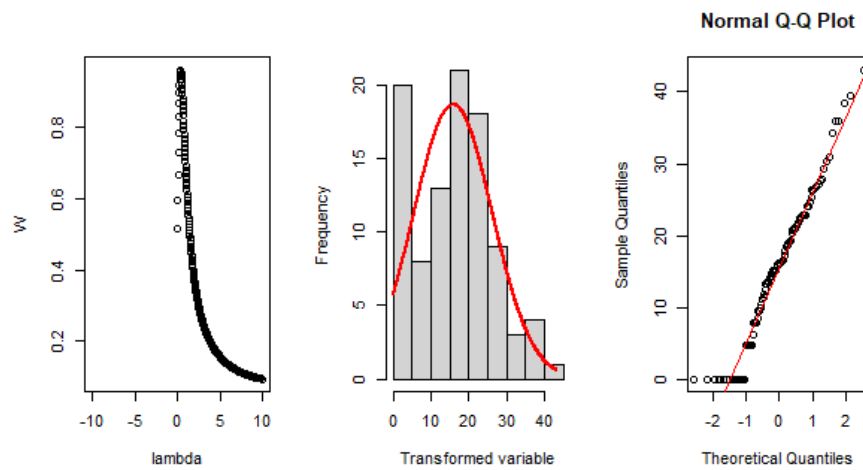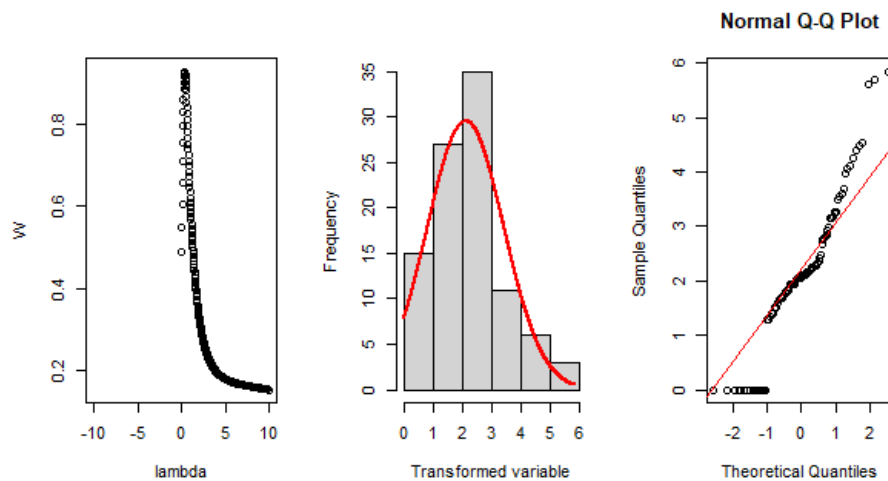

Figure 10: Attempted Tukey transformation ladder results on average woody regeneration height. From left to right: Tested lambda values, transformed data histogram, and QQ plot comparing the transformed data to a Gaussian distribution.

Table 2: P-values from Kruskal-Wallis tests.

Legacy/Topographic Variable	Kruskal-Wallis p-value (Density)	Kruskal-Wallis p-value (Performance)
Aspect	0.1596	0.1167
Slope	7.161×10^{-6}	1.222×10^{-7}
Elevation	3.401×10^{-8}	2.133×10^{-13}
Deadwood Volume	0.00477	0.09048
Vegetative Cover	0.001488	0.001521
Leaf litter Cover	0.04337	4.489×10^{-5}
Rocky Cover	0.7392	0.009078
Soil Cover	0.00377	7.596×10^{-7}

Given these results from the Kruskal-Wallis analysis, Dunn tests were applied to understand the effects of slope, elevation, vegetative cover, leaf litter cover, and soil cover on regeneration density and performance. Rocky cover was analysed only with respect to regeneration performance. See Table 3 for results of the Dunn tests.

In terms of slope, regeneration density showed a general decrease with increasing slope (Figure 11) between flat and moderate slopes ($p<0.001$), and flat and steep slopes ($p<0.00002$), but no significant difference was found between moderate and steep slopes ($p>0.09$).

Regeneration performance had a similar relationship, but with a significant difference between
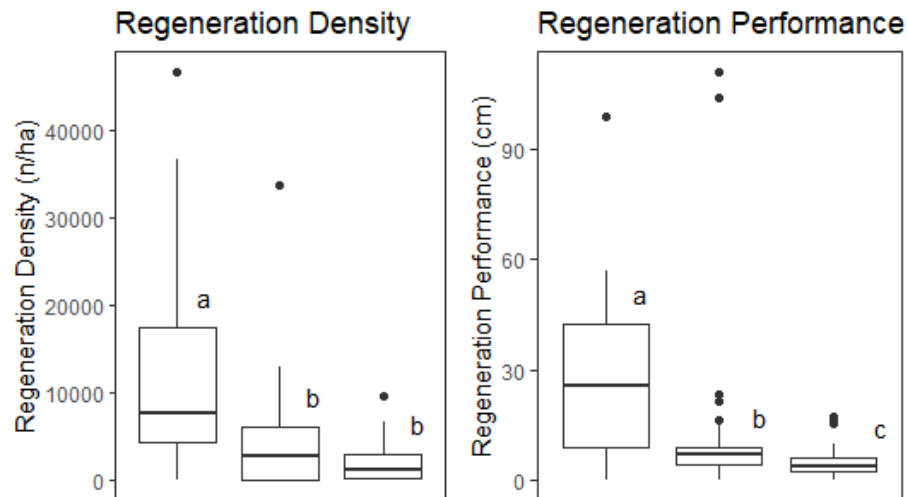
Figure 11: Woody regeneration density and performance response to slope.

performance between all slope categories; Flat and moderate slopes ($p<0.0003$), moderate and steep slopes ($p<0.03$), and flat and steep slopes ($p<5 \times 10^{-6}$).

Different elevations also showed a significant response, with the general trend of higher density and performance at lower elevation (Figure 12). All elevation bands showed significant differences in regeneration density except between the low elevation band and the medium elevation band (p>0.7). Similarly, most elevation bands showed significant differences in regeneration performance except the difference between low elevation plots and medium elevation plots (p>0.3), and between medium elevation plots and high elevation plots (p>0.06).
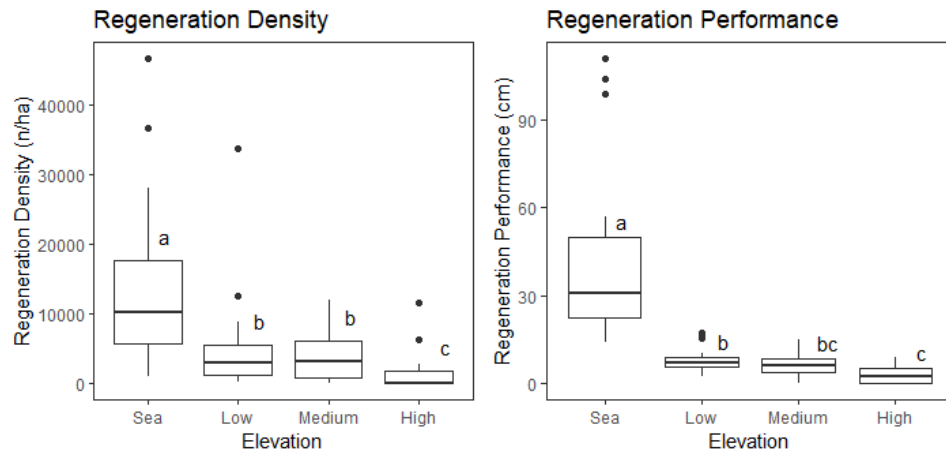
Figure 12: Woody regeneration density and performance in response to elevation.
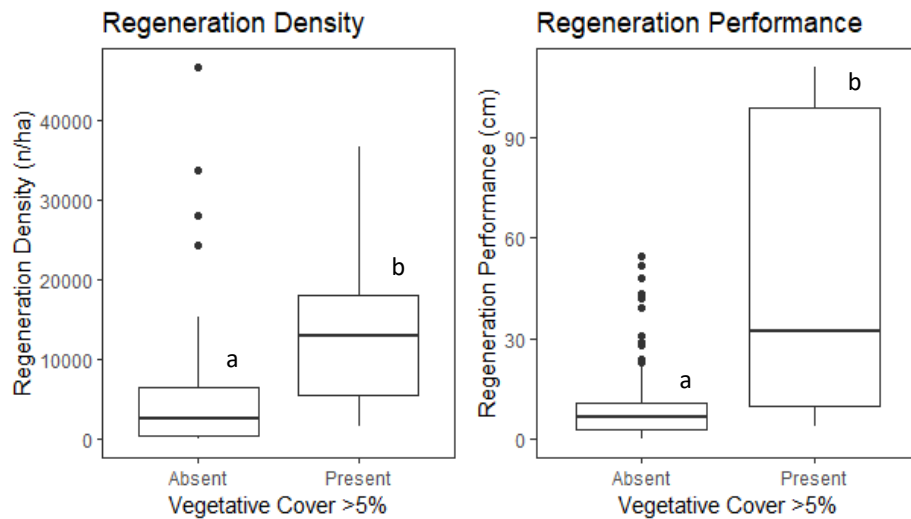
Figure 13: Woody regeneration density and performance response to vegetative cover over 5%.
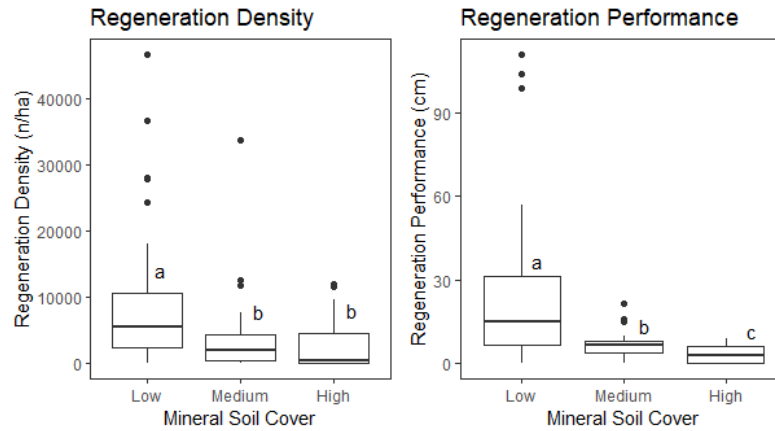
Figure 14: Woody regeneration density and performance response to soil cover.
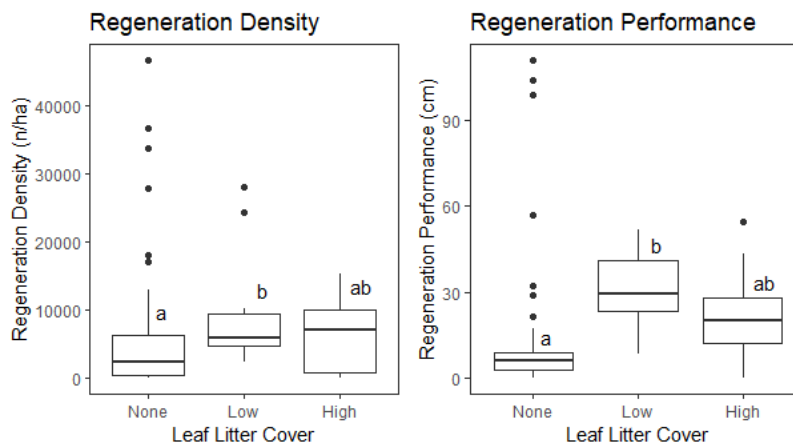
Figure 15: Woody regeneration density and performance response to leaf litter cover.
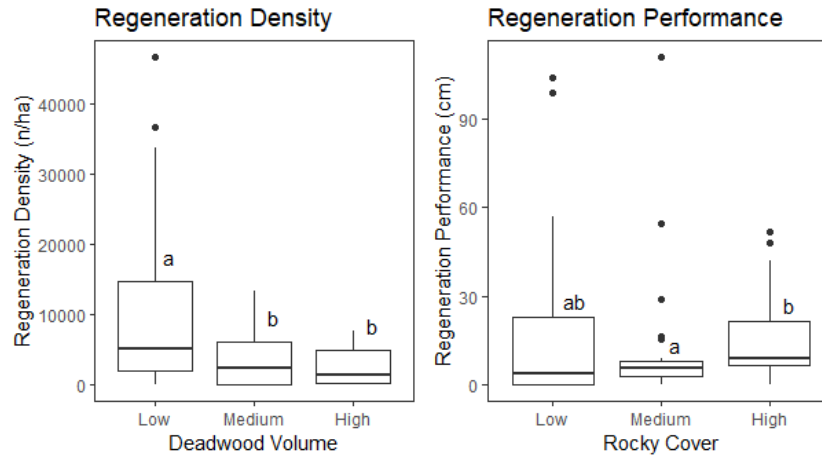
Figure 16: Woody regeneration density response to deadwood volume and regeneration performance response to rocky cover.

Vegetative cover (Figure 13) showed a significantly higher level of both woody regeneration density and performance with the presence of vegetative cover over 5% ($p<2.2\text{x}10^{-16}$). The other ground cover legacies did not show as strong a response; density and performance were lower with mineral soil cover (Figure 14) between low to medium cover ($p<0.03$ and

p<0.0025, respectively) and low to high cover (p<0.008 and $p<1\times10^{-6}$, respectively). Density showed no response between medium and high cover (p>0.4), but performance saw a statistically significant decrease (p<0.04). Both density and performance showed a positive relationship with leaf litter cover (Figure 15), but only between plots with no leaf litter cover and low leaf litter cover (p<0.05 and $p<8.5\times10^{-5}$, respectively). The comparison between low and high leaf litter cover had no significance for either response variable (p>0.09 in all cases). Rocky cover was only analysed with respect to regeneration performance (Figure 16) and a trend of greater performance only when comparing low and medium cover plots (p<0.012). Regeneration density had a negative relationship between plots with low to medium deadwood volume (p<0.033) and between low and high-volume plots (p<0.0058) (Figure 16).

Table 3: Dunn test p-values for regeneration density and performance by site characteristics.

Site Characteristic	Density p-value	Performance p-value
Slope		
Flat (≤10%) vs Moderate (≤20%)	$9.298988ex10^{-4}$	$2.133879x10^{-4}$
Moderate vs steep (>20%)	$9.127611x10^{-2}$	$2.810659x10^{-2}$
Flat vs steep	$4.605258x10^{-6}$	$6.20514x10^{-8}$
Elevation		
Sea(<100m) vs Low (<400m)	$6.318415x10^{-3}$	$1.72287x10^{-5}$
Low vs Medium (<437m)	$7.971470x10^{-1}$	$3.421490x10^{-1}$
Medium vs High (≥437m)	$9.311209x10^{-3}$	$6.127371x10^{-2}$
Sea vs Medium	$4.897744x10^{-3}$	$2.113461x10^{-7}$
Sea vs High	$5.334450x10^{-9}$	$1.002497x10^{-13}$
Low vs High	$7.259223x10^{-3}$	$5.000830x10^{-3}$
Vegetative Cover		
Absent (≤5%) vs Present (>5%)	$<2.2x10^{-16}$	$<2.2x10^{-16}$
Rock Cover		
Low (<35%) vs. Medium (<60%)		$8.2382295x10^{-1}$
Medium vs High (≥60%)		$1.183034x10^{-2}$
Low vs High		$7.682028x10^{-2}$
Leaf litter Cover		
None (0%) vs Low (<50%)	$4.883884x10^{-2}$	$8.454337x10^{-5}$
Low vs High (≥50%)	$6.7721736x10^{-1}$	$1.605029x10^{-1}$
None vs High	$3.4205178x10^{-1}$	$9.225847x10^{-2}$
Soil Cover		
Low (<35%) vs Medium (<60%)	$2.6259528x10^{-2}$	$2.471512x10^{-3}$
Medium vs High (≥60%)	$4.37321543x10^{-1}$	$3.150566x10^{-2}$
Low vs High	$8.232921x10^{-3}$	$9.820951x10^{-7}$
Deadwood Volume		
Low (<2.3m^3) vs Medium (<3.9m^3)	$3.2800210x10^{-2}$	
Medium vs High (≥3.9m^3)	$5.04478976x10^{-1}$	
Low vs High	$5.774887x10^{-3}$	

Density and Performance of Regenerative Strategies

The three regenerative strategies—obligate seeder, obligate resprouter, and facultative seeder—were analysed separately. Observing the general shape of the data, facultative seeders are the most successful strategy immediately after severe fire (Figure 17), with the highest average density of 3359 stems per hectare. This is followed by obligate resprouters (Figure 18), with an average density of 2043 stems per hectare. Lastly, obligate seeders (Figure 19) had the lowest average density at 416.6 stems per hectare. Performance followed a slightly different trend, as resprouters averaged of 13.78cm in each plot, followed by facultative performance
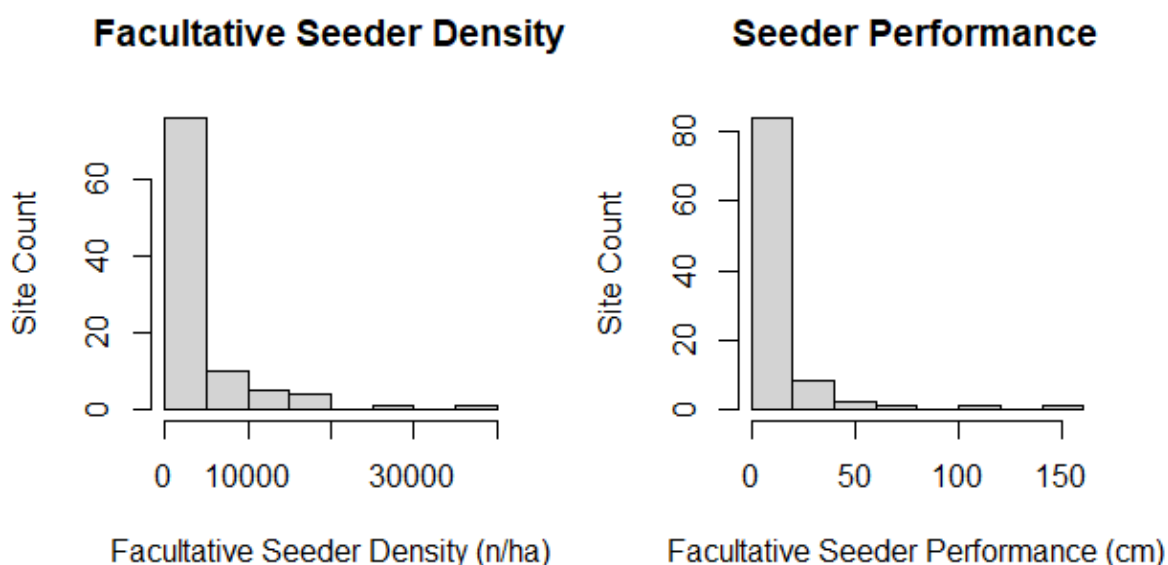
Figure 17: Facultative seeder density and performance histograms.
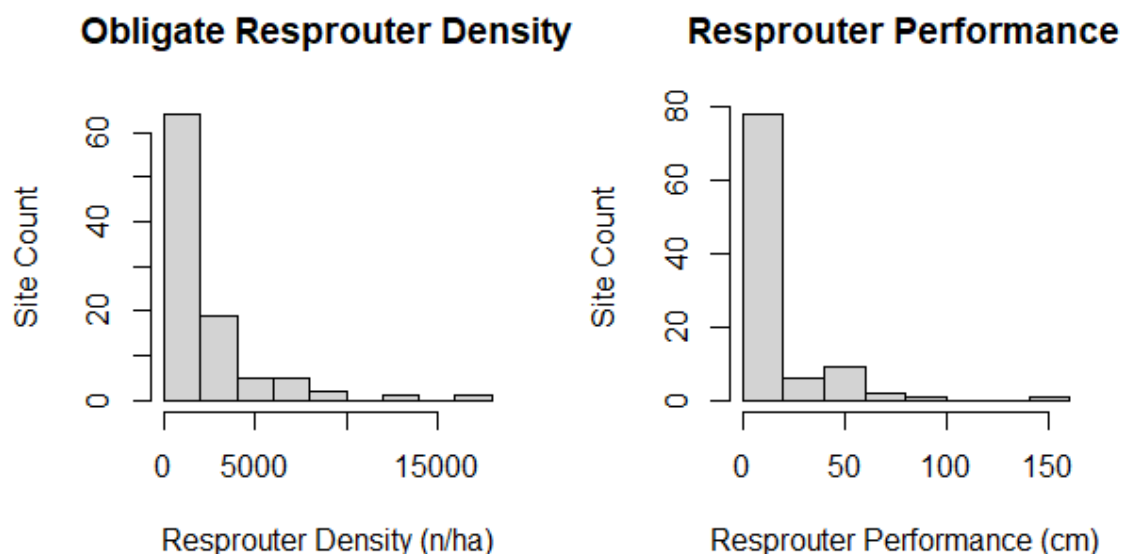
Figure 18: Obligate resprouter density and performance histograms.
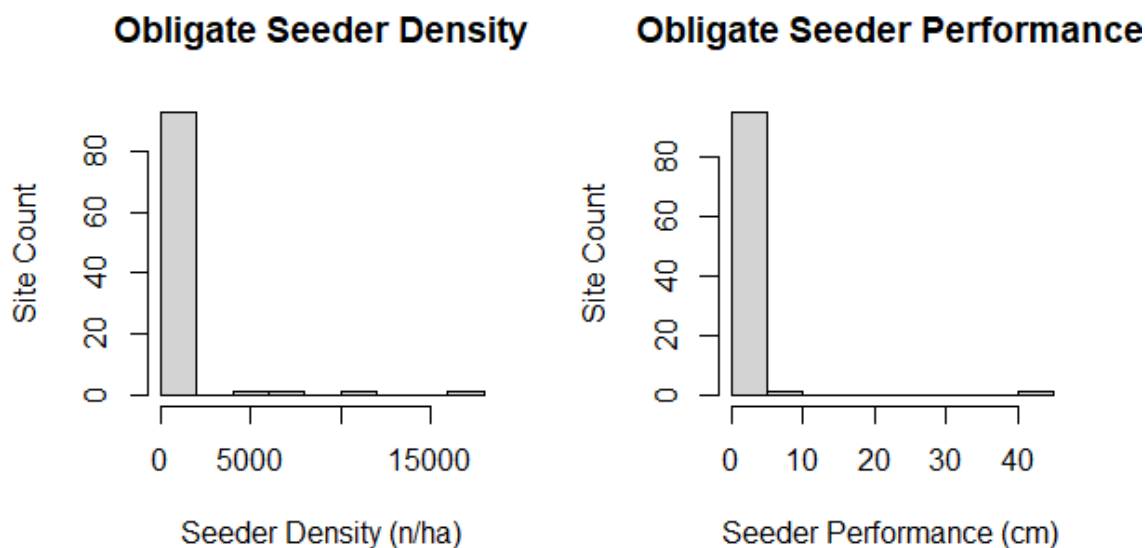
Figure 19: Obligate Seeder density and performance histograms.

(11.19 cm on average), and lastly by obligate seeders with an average height of 0.7cm. Obligate seeders were present in only 8 of the 97 sites, and were excluded from the rest of the analysis.

As with the total regeneration density and performance data, these datasets were too right skewed to proceed with parametric statistical tests. Non-parametric Kruskal-Wallis tests and Dunn tests were conducted on the data to determine the relationship between each group and the topographic characteristics and material legacies. The results of the Kruskal-Wallis tests are in Table 4. There were few universal trends with respect to the relationship between site conditions and the density or performance of each group. All results from the subsequent Dunn tests can be found in Table 5.

Table 4: Kruskal-Wallis Results for regenerative strategies.

Site Condition	Obligate Seeders		Obligate Resprouters		Facultative Seeders	
	Density	Performance	Density	Performance	Density	Performance
Aspect	0.07385	0.07083	0.8325	0.6483	0.007256	0.009749
Slope	0.06384	0.08052	4.075×10^{-4}	1.179×10^{-5}	0.01571	0.001051
Elevation	0.00370	0.00439	7.234×10^{-5}	1.179×10^{-10}	7.68×10^{-5}	1.887×10^{-7}
Deadwood Volume	0.04013	0.04524	0.02479	0.05909	0.06114	0.06596
Vegetative Cover	0.1061	0.1061	0.2007	0.009242	0.002283	0.001397
Leaf litter Cover	0.8393	0.8518	0.02165	9.017×10^{-5}	0.1418	0.04661
Rocky Cover	0.6876	0.6339	0.4642	0.1548	0.5711	0.03085
Soil Cover	0.1861	0.2227	0.002519	7.963×10^{-7}	0.2785	6.889×10^{-4}

The only constant significant relationship among all groups is the affect of elevation on density and performance (p<0.003 in all cases). Slope affects both density and performance of obligate resprouters as well as facultative seeders (p<0.02). Aspect had an effect only on the density and performance of facultative seeders (p<0.01). Deadwood volume affected the density and performance of obligate seeder (p<0.05) and the density of obligate resprouters (p<0.05) but had no effect on any other metric. Conversely, vegetative cover had no effect on obligate seeder density, performance, nor obligate resprouter density, but the relationship was significant for all other response variables (p<0.01). leaf litter cover was significant only for obligate resprouter density and performance, and facultative seeder performance (p<0.05). Rocky cover was unimportant across all metrics except for the performance of facultative seeders (p<0.035). Mineral soil cover affected both density and performance of obligate resprouters and the performance of facultative seeders (p<0.003).
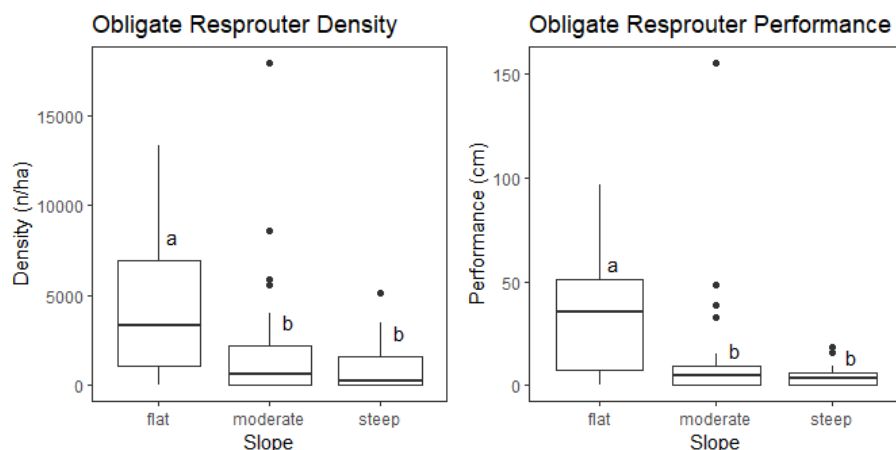
Figure 20: Obligate resprouter density and performance response to slope.
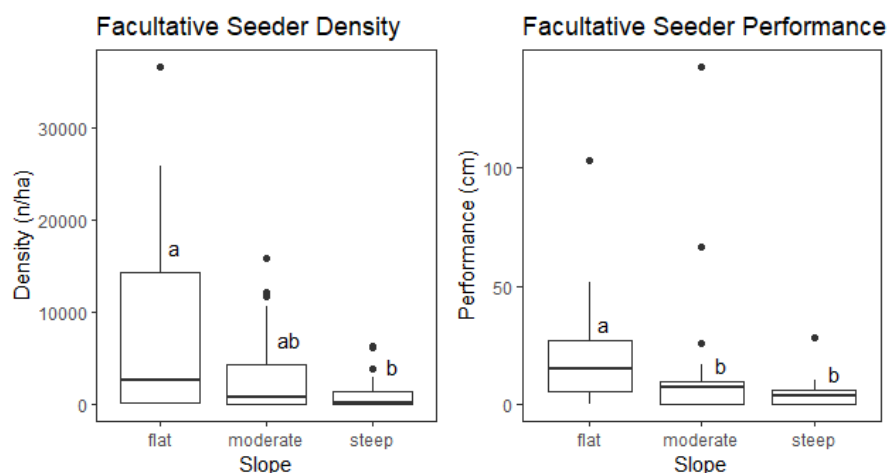
Figure 21: Facultative seeder density and performance response to slope.

Both obligate resprouters and facultative seeders tended to have lower density and shorter stems as the gradient became more extreme (Figures 20 & 21), though only when comparing flat and moderate or flat and steep gradients for obligate resprouters (p<0.005), density of facultative seeders on flat and steep gradients, and performance of facultative seeders between flat and

moderate gradients or flat and steep gradients (p<0.015). Elevation showed a similar relationship, with higher elevations corresponding to lower density and performance of both obligate resprouters (Figure 22) and facultative seeders (Figure 23). Obligate resprouter density was significantly lower only between sea level and high elevations (p<0.001). Resprouter performance was significantly lower as elevation increased, except when comparing low and medium elevation (p>0.25), and medium and high elevation (p>0.1). Facultative seeder density was significantly different between low and high elevation (p<0.005) and sea level and high elevation (p<0.0001). Facultative seeder performance likewise decreased in response to higher elevation bands. Significantly shorter stems were found between sea and low elevation
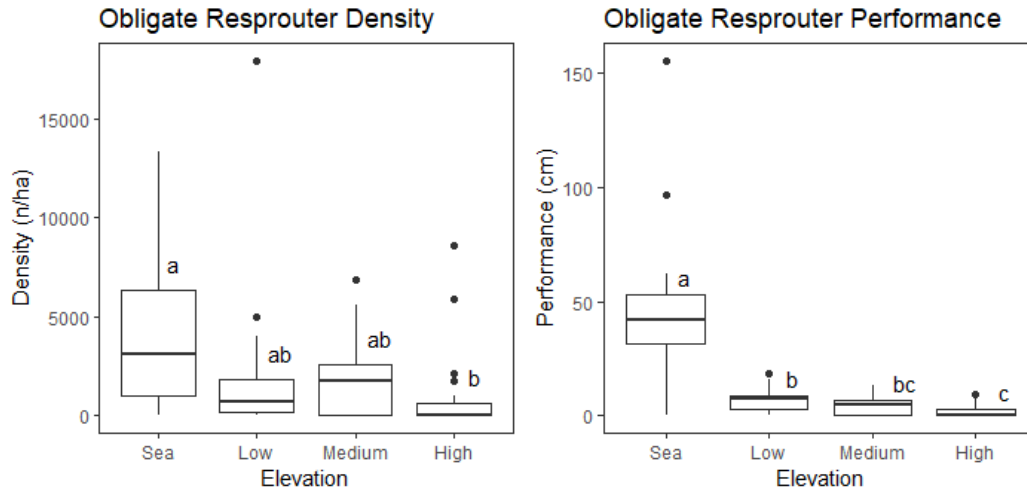
Figure 22: Obligate resprouter density and performance response to elevation.
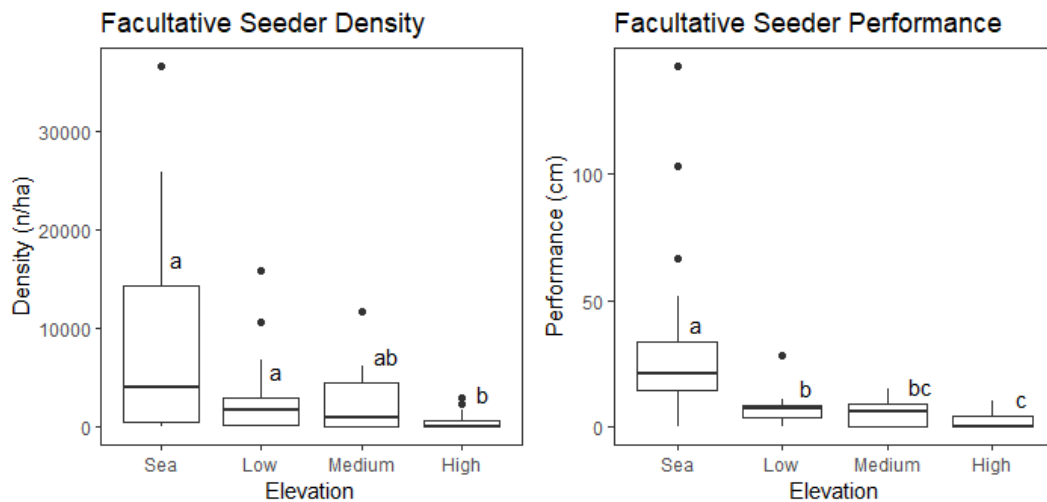
Figure 23: Facultative seeder density and performance response to elevation.

(p<0.015), between sea and high elevation (p<0.0001), and low and high elevation (p<0.015).

Aspect only had and effect on facultative seeder regeneration (Figure 24). Density did not vary significantly between the ordinals, except for a difference between northwest-facing and

both northeast and southeast-facing slopes (p<0.04). Performance followed the same trend as density with respect to plot orientation.
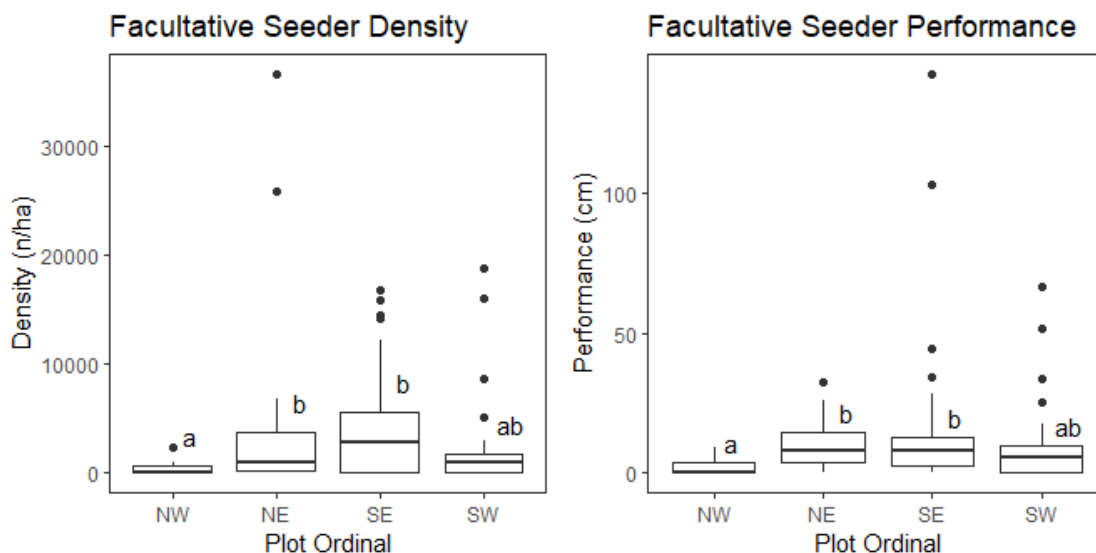
Figure 24: Facultative seeder density and performance response to plot orientation.

Facultative seeder density and performance increased significantly with respect to the presence vegetative cover (Figure 25). While vegetative cover had no influence on the density of obligate resprouters, their performance also benefitted from the presence of vegetative cover (Figure 26). Conversely, deadwood volume had no affect on obligate resprouter performance, but density was higher in plots with more deadwood present (Figure 26).
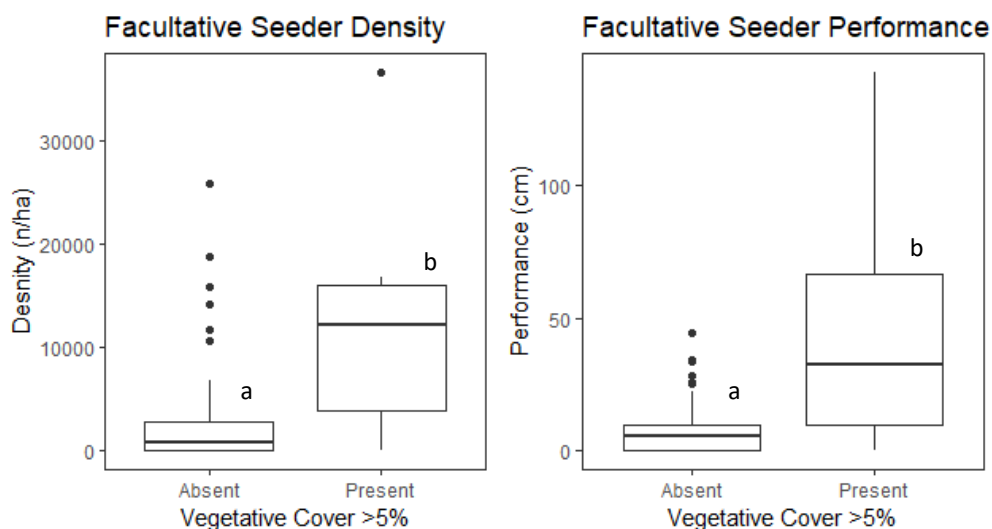
Figure 25: Facultative seeder density and performance response to vegetative cover.
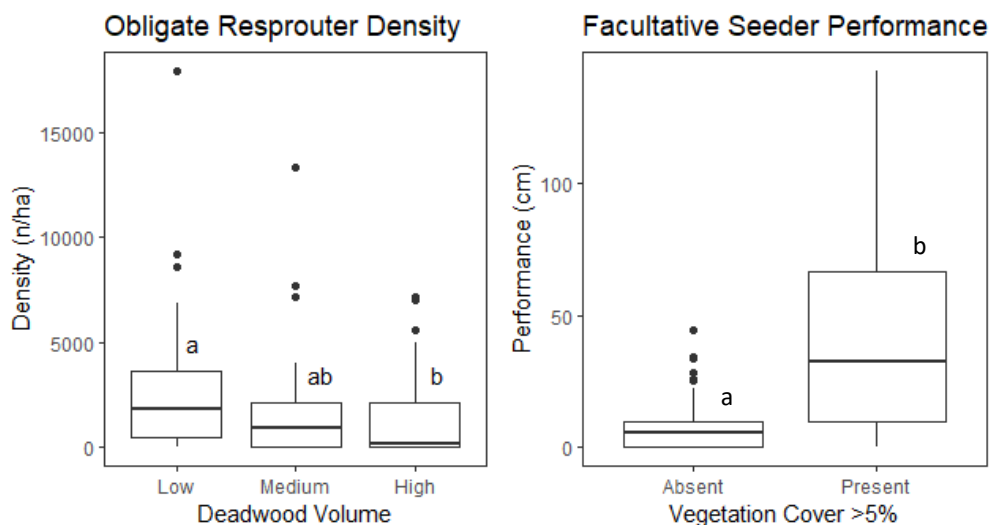
Figure 26: Obligate resprouter density response to deadwood and performance response to vegetative cover.

Obligate resprouter density and performance were affected by leaf litter (Figure 27); there was a significant increase in density and greater performance between plots with no litter and low litter cover (p<0.035). There was a similar relationship between resprouter density and performance and soil cover (Figure 28). Plots with low soil cover had greater regeneration density and performance when compared to medium soil cover (p<0.001). This was also the case between plots with low and high soil cover (p<0.015).
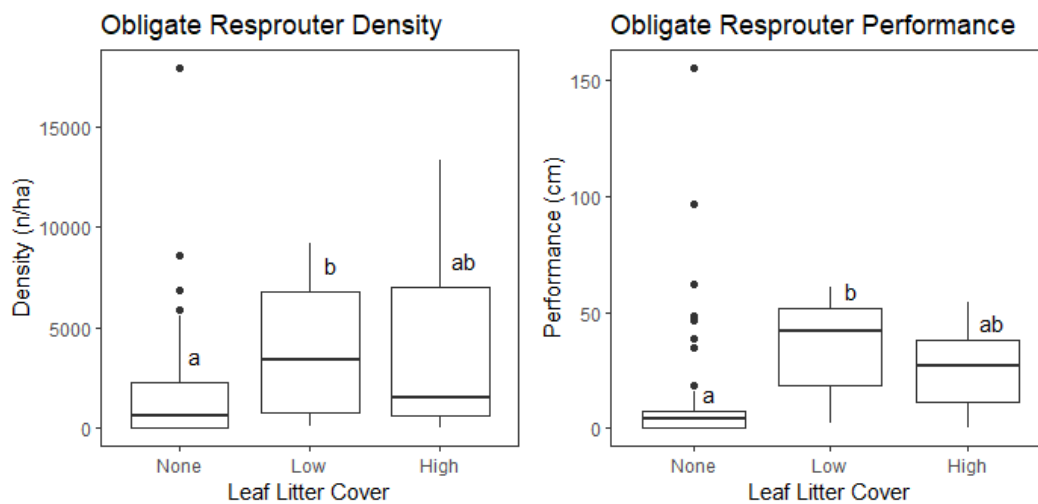
Figure 27: Obligate resprouter density and performance response to leaf litter cover.
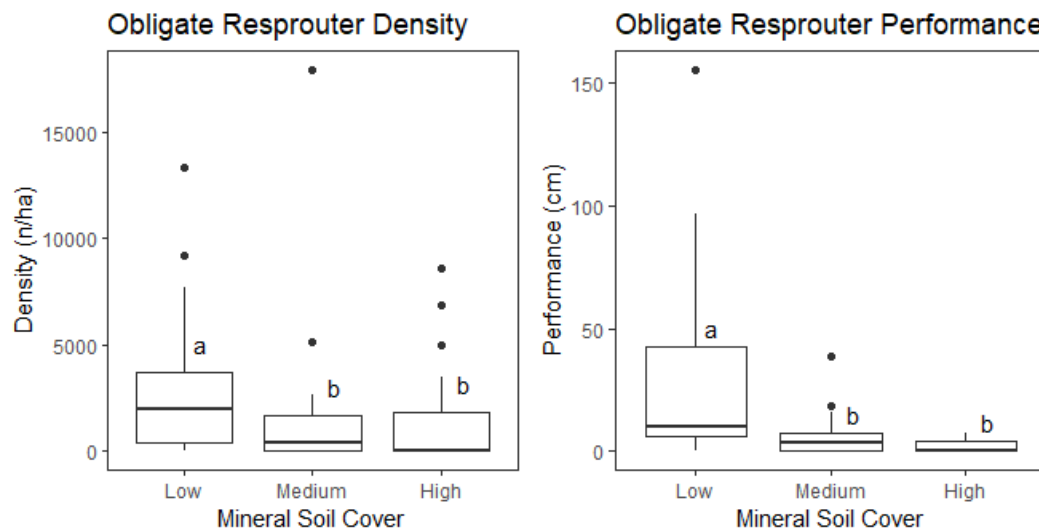
Figure 28: Obligate resprouter density and performance response to mineral soil cover.

Facultative seeder species performance was affected significantly by groundcover variables (Figure 29), as density did not vary significantly with rocky cover, soil cover, or leaf litter cover. Performance was supported by higher rock cover, with a significant increase between plots with medium and elevated levels of rocky cover ($p<0.035$). An increase from no leaf litter to low cover also appears to benefit performance of facultative seeders ($p<0.04$). Facultative seeder performance followed the overarching trend of lower height averages with increased soil cover, particularly between low and medium plots ($p<0.045$) and low and high plots ($p<0.001$).
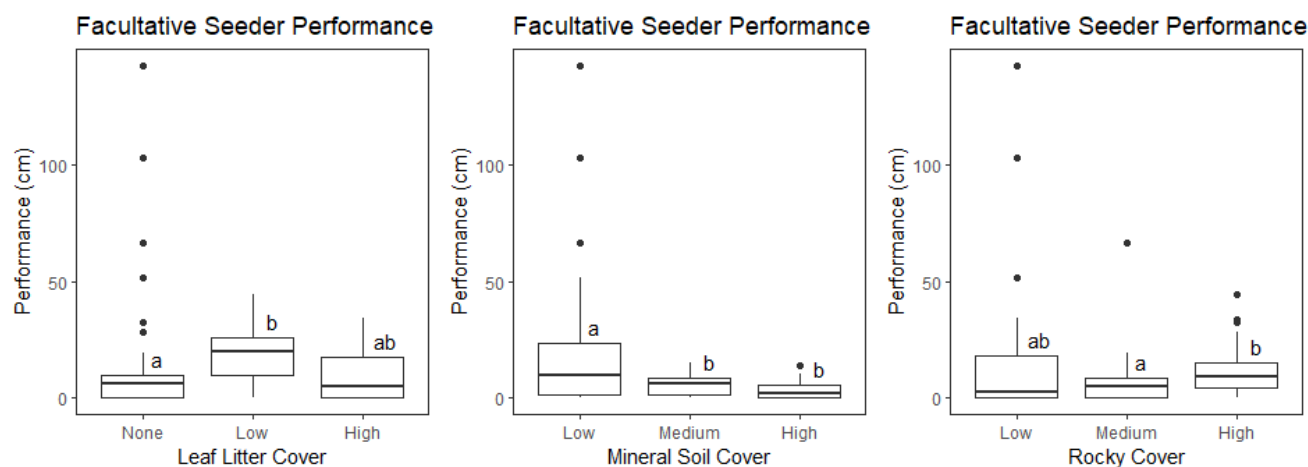
Figure 29: Facultative seeder performance response to leaf litter, mineral soil, and rocky cover

Table 5: Dunn Test p-values for obligate resprouters and facultative seeders.

Site Characteristic	Obligate Resprouters		Facultative Seeders	
	Density p-value	Performance p-value	Density p-value	Performance p-value
Slope				
Flat (≤10%) vs Moderate (≤20%)	0.00404190	0.0005293656	0.14263783	0.01190686
Moderate vs Steep (>20%)	0.30984749	0.1808298	0.18265251	0.0732737875
Flat vs Steep	0.00039160	0.0000104132	0.01190686	0.0006383136
Elevation				
Sea(<100m) vs Low (<400m)	0.06257780	0.002703823	0.4686394205	0.01265242
Low vs Medium (<437m)	0.9451476	0.2895312	0.3852952156	0.4210479
Medium vs High (≥437m)	0.7108308	0.1479339	0.0592560107	0.08296782
Sea vs Medium	0.06463313	3.135245×10^{-6}	0.1277204084	0.00134678
Sea vs High	0.0000183749	6.298430×10^{-11}	0.0000495624	4.938242×10^{-8}
Low vs High	0.05338626	0.01210313	0.0041990984	0.01220826
Aspect				
NW vs NE			0.035454739	0.016094018
NE vs SE			0.579663870	0.976187391
NW vs SE			0.005663837	0.009867295
SW vs NE			0.588006164	0.546020269
SW vs NW			0.266228150	0.161126634
SW vs SE			0.264151131	0.660072330
Vegetative Cover				
Absent (≤5%) vs Present (>5%)		$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
Rock Cover				
Low (<35%) vs. Medium (<60%)				0.68287934
Medium vs High (≥60%)				0.03274429
Low vs High				0.21316554
Leaf litter Cover				
None (0%) vs Low (<50%)	0.03125017	0.000260086		0.03984115
Low vs High (≥50%)	0.42855157	0.285171712		0.23246403
None vs High	0.38358561	0.057859560		0.81665098
Soil Cover				

Low (<35%) vs Medium (<60%)	0.00904806	0.0001059587		0.044363053
Medium vs High (≥60%)	0.88677258	0.2833171		0.112780882
Low vs High	0.01195707	8.744295×10^{-6}		0.000692405
Deadwood Volume				
Low (<2.3m^3) vs Medium (<3.9m^3)	0.17346319			
Medium vs High (≥3.9m^3)	0.35399880			
Low vs High	0.02239029			

Discussion

This study investigates the material legacies and topographic characteristics of severely burnt *Pinus nigra* stands, as well as the characteristics of woody regeneration within the first year after fire. The microsites created by these characteristics affect the density and performance of woody vegetation without anthropogenic intervention in the first year following disturbance. The simple survey methodology is flexible enough to be used in similar studies across a wide range of landscapes.

Topographic factors can facilitate microclimatic conditions that foster or hinder natural regeneration. The bimodal shape of the elevation distribution corresponded with our sampling locations: the sea level plots were in the Monfalcone municipality in Italy. The higher elevation plots were in Slovenia. Increasing elevation shows a negative correlation with woody regeneration density and performance. This response corresponds with decreased species diversity explained by extending Rapports latitudinal rule to an elevation gradient (Stevens, 1992). The harsher, more exposed elevations may contribute to conditions unsuitable for the early regeneration of woody vegetation. Slope also showed a similar response, with decreased density and performance corresponding to more extreme slope. Considering the geological characteristics of the Karst Plateau (Hajna, 2003), steeper slopes may correspond to reduced water retention (McCain & Grytnes, 2010), as any precipitation quickly flows downhill and drains through the carbonate bedrock. This is reflected in the significant difference between performance of regeneration in each slope category. There may be enough moisture for regeneration to establish on steep slopes, but the decreased performance on more extreme gradients is indicative of a limiting factor tied to slope. Surprisingly, plot aspect did not show a significant effect on neither density nor performance. Southern plots were expected to show greater density and performance due to warmer (Wani et al., 2023), wetter conditions facilitated by the Adriatic (McCain & Grytnes, 2010). However, the Karst Plateau is climactically separated from the Adriatic by its steep western ridge (Hajna, 2003), so it is possible that the only advantage of south-facing slopes is the increased solar exposure. It may be that the disadvantageous cooler temperatures on northern slopes are counterbalanced by overexposure to solar radiation on the southern slopes, creating two equally inhibiting factors.

When considering topography overall, woody regeneration is fostered at lower elevation, with flatter slopes which can provide greater water retention and have potential for greater accumulation of organic matter. After a certain point the intensity of this gradient appears to wane, which follows the "unimodal hump" seen along elevational gradients with respect to species density and diversity (Dani et al., 2023). These conclusions are drawn from prevailing assumptions about the elevational gradient (Dani et al., 2023; McCain & Grytnes, 2010; Wani et al., 2023). Further research and modelling will better define the relationship among topographic variables, particularly with respect to aspect, which is considered as a key factor in vegetative diversity and performance (Wani et al., 2023).

While topographic variables are important in creating predictable microclimatic conditions that effect regeneration density and performance, the material legacies remaining after fire create heterogeneity that can support or restrict regeneration (Johnstone et al., 2016). Vegetative cover corresponded with higher density and performance of woody vegetation regeneration. This is confirmed by other studies, which also found that greater herbaceous cover can reduce heat stress, increase soil moisture, and regulate variation in temperature (Christopoulou et al., 2014; Ordónez et al., 2004). This facilitation by the understory is particularly important in black pine forests, as the autosuccession pathway is unlikely due to black pine's lack of adaptation to fire (Arnan et al., 2007; Martín-Alcón & Coll, 2016; Ordónez et al., 2004). Vegetative cover may increase water availability for resprouting woody vegetation (Arnan et al., 2007), particularly in the well-drained soils of the Karst Plateau. However, sites with significant vegetative cover within a year post-fire may be situated in microsites that support regrowth either because of topography or other material legacies. It is also possible that these areas experienced less severe ground fire than other survey patches. More research may be able to disentangle these effects.

Non-living ground cover also creates conditions conducive to regeneration of woody vegetation. The only clear relationship came from the comparison between plots with no leaf litter cover and plots with low leaf litter cover. Plots with no cover showed no significant difference with plots with high cover. Plots with no leaf litter had lower regeneration density and reduced performance compared to the sites with less than 50% cover. Leaf litter regulates light availability, moisture, and temperature at the soil surface, reducing light and potentially intercepting precipitation. This can create microsites that reduce the probability of germination or establishment of regeneration (Flagler et al., 1991). Low levels of leaf litter may reduce the intensity of insolation, particularly on exposed forest floors post crown fire, but elevated levels may cross a facultative threshold and create suboptimal conditions for regeneration of woody vegetation. The strength of this relationship could be revealed through modelling and further research monitoring specific physical and chemical aspects of microsites associated with leaf litter cover.

Rocky cover was another factor in the facilitation of woody regeneration performance but had no effect on regeneration density. The relationship between rocky cover and regeneration height is not particularly strong, only seeing a significant difference between plots with medium and high cover. Rocky cover facilitates greater performance, perhaps as it provides a minor

shelter from browsing and other small-scale disturbances. Stonier soils have a lower water capacity, potentially impacting regeneration performance. This does not explain the observed trend of higher regeneration and greater performance. Most sites had prominent levels of rock cover (Figure 6), paired with the severity of fire may explain the lack of regeneration and therefore the lack of significance with respect to regeneration density.

Mineral soil cover is an interesting factor, as it the presence of bare soil can be considered as the absence of material legacies. The findings from this study support this conclusion, as both regeneration density and performance decreased significantly with increasing soil cover—except in the case of regeneration density from low to medium cover plots, which showed no significant relationship. As discussed before, the soils in this area are moisture limited due to the region's geography. Mineral soil provides little temperature regulation at the surface, does little in the way of moisture retention, and is more susceptible to erosion, particularly on steeper slopes (López-Vicente et al., 2021). Erosion is a concern in this area and may have resulted in higher levels of mineral soil cover. The erosion at higher elevation bands may impact natural regeneration at lower bands by burying or dislodging resprouting stems. This relationship between mineral soil and reduced density and performance supports the hypothesis that material legacies post-fire are crucial factors in supporting the natural regeneration of woody vegetation, as they create conditions post-fire that regulate temperature and moisture and may play a role in reducing stress and damage from erosion.

The types of woody regeneration present give some insight into potential successional pathways after a severe fire in black pine forests. Obligate seeders such as those listed in Table 1 were present in less than 10% of the sample plots. Given the high severity of the fire and the lack of serotiny in the pre-disturbance community, this result emphasizes the need for this study; working to predict how severe fire will alter these unmanaged landscapes. These regeneration strategies are the informational legacies in these ecosystems and comprise the second aspect of ecological memory (Johnstone et al., 2016). As observed in other studies (Keeley et al., 2006; Vasques et al., 2023), facultative seeders appear to have an early successional advantage post-fire in terms of regeneration density. Obligate resprouters showed the greatest average performance of regeneration, rather than facultative seeders. This may be due to inter-species competition, as resprouters have the ability to hinder the growth of nearby individuals when resources are limited (Sánchez-pinillos et al., 2018). Although facultative seeders may have the advantage in colonising optimal microsites, when they must compete with resprouting species the resprouters appear to be at an advantage.

Both facultative seeders and obligate resprouters followed similar trends as overall density and performance with respect to material legacies and topography. Lower elevations, milder slopes, presence of vegetative cover, and leaf litter cover supported greater densities in both groups. The influence of site aspect was only important for facultative seeder density and performance. The northwest- and southwest-facing plots had the lowest densities and performance; the other ordinals were not significantly different. A significant difference was anticipated between the southern slopes and northern slopes (McCain & Grytnes, 2010), but the deciding factor appears to be an east/west division. The unique geography of the Karst Plateau

may have influenced this finding and more research into factors affecting insolation in the area is recommended.

In general, the findings of this study support the hypothesis that material legacies and topography create conditions conducive to natural regeneration of woody vegetation, through the regulation of light availability, temperature, and soil moisture. One surprising result was the relationship between deadwood and regeneration density—including obligate resprouters—along with the lack of a relationship between deadwood and regeneration height. Many studies have found that downed woody debris is incredibly important in the establishment and performance of regeneration, particularly post-fire (López-Vicente et al., 2021; Mantero et al., 2023; Marcolin et al., 2019). This relationship is already under analysed in contemporary studies that focus on effects of salvage logging post-fire is studied in the Mediterranean (Mantero et al., 2023; Marcolin et al., 2019). This study provides a starting point for further modelling and investigation of early regeneration pathways following severe fire in non-fire adapted pine plantations. In further studies, survivorship and rate of growth could be considered as a long-term study, as well as classification of material legacies into more specific classes (downed vs standing deadwood, for example).

These findings can help aid in the development of management decisions following severe fire. The importance of material legacies and the topography of affected areas is clear; land managers and decision makers should survey areas in question to determine which areas may support natural regeneration. Of course, the goals of regeneration must be kept in mind. black pine plantations are unlikely to recover as black pine stands, instead converting to shrubland or open-oak forests. As timber from black pine stands is not currently an important market for Italy, this conversion to oak forest or shrubland may not conflict with management goals for the Karst Plateau. The increased risk of erosion following severe fire (Walker et al., 2013), particularly in Karst, should be considered. Reforestation and salvage logging are often destructive processes, resulting in further soil erosion and influencing biodiversity (López-Vicente et al., 2021; Mantero et al., 2023), particularly in pine forests with no natural adaptation to fire (Mantero et al., 2023).

Conclusions

The increasing risk of fire in unmanaged *Pinus nigra* plantations in the Mediterranean poses a significant issue in post-disturbance management. As these plantations have long been abandoned, one pathway for recovery lies in natural regeneration. This study explored the material legacies left after severe fire and their impact on determining the successional pathway given no anthropogenic intervention. Facultative seeders—mainly shrubs—dominate the early successional community but may be outcompeted by resprouting species such as oaks in the medium-long term. Material legacies and topographic characteristics that can regulate temperature and increase soil moisture supported both increased density and performance of woody regeneration, implicating a natural shift to the dominance of shrubs or resprouting oaks after severe burns. Depending on management goals, natural regeneration may be a viable option

for reforestation. Artificial reforestation may not be necessary, especially as these stands tend to no longer be used for timber production. However, erosion may reduce regeneration after severe fire and may require intervention. Salvage logging may seem opportune following large fires, but has been shown to reduce natural regeneration in other studies, especially in the short-term (López-Vicente et al., 2021; Mantero et al., 2023; Marcolin et al., 2019). The material legacies described here could be affected by heavy machinery, particularly vegetative and leaf litter cover, resulting in more disturbed soil cover, which is likely to reduce the density and performance of woody regeneration.

Further research in this area is required to determine the strength of the relationships described here, and long-term studies should be conducted to determine if early natural regeneration is in fact indicative of successional pathways following severe fire.

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Appendix: R Script

```r
### Data analysis of Carso natural regeneration-2023. By Linus Shaw, edits by Flavio Taccaliti

### Load Libraries
library(readxl)

## Warning: package 'readxl' was built under R version 4.2.3

library(tidyverse)

## Warning: package 'tidyverse' was built under R version 4.2.3

## Warning: package 'ggplot2' was built under R version 4.2.3

## Warning: package 'tibble' was built under R version 4.2.3

## Warning: package 'tidyr' was built under R version 4.2.3

## Warning: package 'readr' was built under R version 4.2.3

## Warning: package 'purrr' was built under R version 4.2.3

## Warning: package 'dplyr' was built under R version 4.2.3

## Warning: package 'stringr' was built under R version 4.2.3

## Warning: package 'forcats' was built under R version 4.2.3

## Warning: package 'lubridate' was built under R version 4.2.3

## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.2     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.0
## ✓ ggplot2   3.4.2     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.0
## ✓ purrr     1.0.1
## ── Conflicts ──────────────────────────────────────── tidyverse_conflicts() ──
```

```
## X dplyr::filter() masks stats::filter()
## X dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to bec
ome errors
```

```r
library(berryFunctions)
```

```
## Warning: package 'berryFunctions' was built under R version 4.2.3
```

```
##
## Attaching package: 'berryFunctions'
##
## The following object is masked from 'package:dplyr':
##
##      between
```

```r
library(rcompanion)
```

```
## Warning: package 'rcompanion' was built under R version 4.2.3
```

```r
library(ggpubr)
```

```
## Warning: package 'ggpubr' was built under R version 4.2.3
```

```r
library(FSA)
```

```
## Warning: package 'FSA' was built under R version 4.2.3
```

```
## Registered S3 methods overwritten by 'FSA':
##    method        from
##    confint.boot  car
##    hist.boot     car
## ## FSA v0.9.5. See citation('FSA') if used in publication.
## ## Run fishR() for related website and fishR('IFAR') for related book.
##
## Attaching package: 'FSA'
##
## The following object is masked from 'package:berryFunctions':
##
##      headtail
```

```r
library(agricolae)
```

```
## Warning: package 'agricolae' was built under R version 4.2.3
```

```r
#### Case study-related variables
#Plot size: radius in metres
radius <- 6
#Automatically calculates plot area in m2
surfplot <- pi*radius^2
#Taper constant to calculate volume of standing trees
taper <- 0.5
#In Carso study, all Pinus nigra snags


################################################################################
### Data import and cleaning

#Set directory and import data from csv files
setwd("C:/Users/linus/OneDrive - University of New Brunswick/UniPD/Lingua&Thesis/Data")

#Plots description
```

```r
#CSV with plot-specific descriptions--topo, cover, etc.
sites_df <- data.frame(read_excel("natreg_carso.xlsx", sheet="results")) %>%
  select(ID, deadwood, pieces, type, length, diametre, branches_steres,
         phane, chamae, cwd, rocks, soil, litter, dicot, monocot,
         slope, aspect, elevation
  )


#Regeneration

#CSV with type and count of regeneration in each plot
regen_frame <- data.frame(read_excel("natreg_carso.xlsx", sheet="data-group2-tree_repeat"))
#Check loaded dataframe (comment if unnecessary)
head(regen_frame)

##   ID            species height gamic quantity estimate
## 1 C1 Cotinus_coggygria     32    no       10      yes
## 2 C1 Cotinus_coggygria     46    no        2       no
## 3 C1 Cotinus_coggygria     33    no       10      yes
## 4 C1 Cotinus_coggygria     40    no        5      yes
## 5 C1 Cotinus_coggygria     32    no       12      yes
## 6 C1 Cotinus_coggygria     75    no        5      yes
##                                    PARENT_KEY
## 1 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468
## 2 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468
## 3 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468
## 4 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468
## 5 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468
## 6 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468
##                                                          KEY
## 1 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468/tree_repeat[1]
## 2 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468/tree_repeat[2]
## 3 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468/tree_repeat[3]
## 4 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468/tree_repeat[4]
## 5 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468/tree_repeat[5]
## 6 uuid:ce46c242-4ea1-4bb4-8849-e2facecb1468/tree_repeat[6]

#Deal with NA values in regen_frame -- gamic = 1 shoot
for (i in 1:length(regen_frame$quantity)){
  if (is.na(regen_frame[i,5])){
    regen_frame[i, 5] <- 1
  }
  else
  {}
}


#Select the useful variables of the regeneration dataframe
regen_df <- regen_frame %>% select(ID, species, height, quantity)

#list and number of site IDs
site_num <- sites_df$ID
nplots <- length(site_num)

#Deal with no-count sites in regen_df
z <- 1
i <- 1
while (z < length(site_num) & i < length(regen_df$ID)) {
  #if there is a missing site, add a row and advance both counters by 1
  if (site_num[z] < regen_df[i,1] & site_num[z+1] < regen_df[i,1]){
    z <- z+1
```

```r
    regen_df <- insertRows(regen_df, i, new = 0)
    regen_df[i,1] <- site_num[z]
    regen_df[i, 2] <- NA
    i <- i+1
  }
  #Advance to next site number in site_num
  else if (site_num[z] != regen_df[i,1]){
    z <- z+1
  }
  #Advance to next observation in regen_df
  else{
    i <- i+1
  }
}
#list to get regen count (n) per site
site_regen <- vector(mode='numeric', length=nplots)
#counter variable for site_regen list
y <- 1
#cycle through individual entries and create a sum for each site
for (x in  1:length(regen_df$ID)){
  if(regen_df[x,1] == site_num[[y]]){
    site_regen[[y]] <- site_regen[[y]]+regen_df[x,4]
  }
  else if (y < nplots)
  {
    y <- y+1
    site_regen[[y]] <- site_regen[[y]]+regen_df[x,4]
  }
}
#total count of regenerating veg in each site
sites_df$regen_sum <- unlist(site_regen, use.names = FALSE)
#get an average regeneration count (n/ha) for each site
#divide by plot size to n/m2 then multiply by 10000 for n/ha, round to integer part
sites_df$regen_ha <- as.integer((sites_df$regen_sum/surfplot)*10000)

#find volume of deadwood
volume <- vector(mode='numeric', length = nplots)
for (i in 1:length(sites_df$ID)){
  #total volume of deadwood in m3
  volume[i] <-
    if(is.na(sites_df$type[i])){ 0
      #zero volume if no deadwood present
      }
    else{
        ifelse(sites_df$type[i] == "log",
               #logs calculated as cylinders, measured at median diameter
               ((sites_df$length[i]*((sites_df$diametre[i]/200)^2)*pi))*sites_df$pieces[i],
               #snags calculated with DBH and taper
               ((sites_df$length[i]*((sites_df$diametre[i]/2)^2)*pi)/100)*sites_df$pieces[i]*t
aper
               )
      }
  }

#attach volume to each plot
sites_df$dead_volume_ha <- unlist(volume, use.names = FALSE)

#get species counts per site
#https://www.statology.org/pivot_wider-r/
totals_df<- pivot_wider(regen_df, names_from = 'ID', values_from = 'quantity',
```

```r
                          values_fill = 0, values_fn = sum)
species_df <- aggregate(totals_df[,3:ncol(totals_df)], by = list(totals_df$species), FUN = sum
)
species_df <- species_df %>% rename(Species = Group.1)
species_df$total <- rowSums(species_df[,2:(ncol(species_df)-1)])
#total number of plants per plot
species_df <- species_df %>% bind_rows(summarise_all(.,
                                                ~ if(is.numeric(.)) {
                                                  sum(.)
                                                } else {"Plot_Total"})
                                    )
#add number of plants per plot to sites_df
sites_df$tot_regen <- as.numeric(as.list(species_df[nrow(species_df),2:(ncol(species_df)-1)]))


#repeat the previous process but with height instead of twig count
temp_df<- pivot_wider(regen_df, names_from = 'ID', values_from = 'height',
                      values_fill = NA, values_fn = mean)
#get mean height for each species
heights_df <- aggregate(temp_df[,3:ncol(temp_df)], by = list(temp_df$species), FUN = mean,
                        na.rm = TRUE, na.action = NULL)
heights_df <- heights_df %>% rename(Species = Group.1)
#average height per species across all plots
heights_df$average <- apply(heights_df[,2:(ncol(heights_df)-1)],1,mean, na.rm = TRUE, na.actio
n = NULL)
#Average height of all regeneration in each plot, ignoring non-present(NA) species
heights_df <- heights_df %>% bind_rows(summarise_all(.,
                                                ~if(is.numeric(.)) {
                                                  mean(., na.rm = TRUE, na.action = FALSE
)
                                                } else {"Plot_avg"})
                                    )
for(i in 2:length(heights_df[nrow(heights_df),])){
  if(is.na(heights_df[nrow(heights_df),i])){
    heights_df[nrow(heights_df),i] <- 0
  }
}
#keep it nice and round at 2 decimals
heights_df <- heights_df %>% mutate_if(is.numeric, round, digits = 2)
#add average height per plot to sites_df
sites_df$avg_height <- as.numeric(as.list(heights_df[nrow(heights_df),2:(ncol(heights_df)-1)])
)


#Seeders, resrpouters, and facultative resprouters
seeder_list <- c("Ailanthus_altissima", "Pinus_halepensis", "Pinus_nigra")
resprout_list <- c("Quercus_pubescens", "Quercus_ilex", "Pistacia_lentiscus",
                "Ostrya_carpinifolia", "Fraxinus_ornus")
fac_list <- c("Cotinus_coggygria", "Crataegus_monogyna", "Prunus_mahaleb",
                    "Ligustrum_vulgare", "Rosa_sp", "Rhamnus_alaternus",
                    "Rhamnus_cathartica", "Robinia_pseudoacacia",
                    "Amorpha_fruiticosa")
seeder.h <- vector(mode="numeric", length = nplots)
seeder.n <- vector(mode="numeric", length = nplots)
resprout.h <- vector(mode="numeric", length = nplots)
resprout.n <- vector(mode="numeric", length = nplots)
fac.h <- vector(mode="numeric", length = nplots)
fac.n <- vector(mode="numeric", length = nplots)


for (i in 2:(ncol(heights_df)-1)){
  seeder_tally <- 0
  resprout_tally <- 0
```

```
  fac_tally <- 0
  for(x in 1:(nrow(heights_df)-1)){
    if(!is.na(heights_df[x,i])){
    if((heights_df[x,1] %in% seeder_list)){
      seeder.h[i-1] <- seeder.h[i-1] + heights_df[x,i]
      seeder.n[i-1] <- seeder.n[i-1] + species_df[x,i]
      seeder_tally <- seeder_tally + 1
    }
    else if((heights_df[x,1] %in% resprout_list)){
      resprout.h[i-1] <- resprout.h[i-1] + heights_df[x,i]
      resprout.n[i-1] <- resprout.n[i-1] + species_df[x,i]
      resprout_tally <- resprout_tally + 1
    }
    else if((heights_df[x,1] %in% fac_list)){
      fac.h[i-1] <- fac.h[i-1] + heights_df[x,i]
      fac.n[i-1] <- fac.n[i-1] + species_df[x,i]
      fac_tally <- fac_tally + 1
    }
    }
  }
  seeder.n[i-1]<- as.integer((seeder.n[i-1]/surfplot)*10000)
  resprout.n[i-1]<- as.integer((resprout.n[i-1]/surfplot)*10000)
  fac.n[i-1]<- as.integer((fac.n[i-1]/surfplot)*10000)
  seeder.h[i-1] <- round((seeder.h[i-1]/seeder_tally), digits = 2)
  resprout.h[i-1] <- round((resprout.h[i-1]/resprout_tally), digits = 2)
  fac.h[i-1] <- round((fac.h[i-1]/fac_tally), digits = 2)
  if(is.na(seeder.h[i-1])){
    seeder.h[i-1] <- 0
  }
  if(is.na(resprout.h[i-1])){
    resprout.h[i-1] <- 0
  }
  if(is.na(fac.h[i-1])){
    fac.h[i-1] <- 0
  }
}
sites_df$seeder_nha <- seeder.n
sites_df$seeder_avgh <- seeder.h
sites_df$resprout_nha <- resprout.n
sites_df$resprout_avgh <- resprout.h
sites_df$fac_nha <- fac.n
sites_df$fac_avgh <- fac.h

# check the dataset used for analyses
head(sites_df)

##    ID deadwood pieces type length diametre branches_steres phane chamae cwd
## 1 C1      yes      3  log      5       15                      0    45      5  10
## 2 C2      yes      1  log      4       15                      2    45     15  10
## 3 C3      yes      2  log      6       16                      1    75      0  10
## 4 C4      yes      2  log      6       24                      2    40     10   5
## 5 C5      yes      3 snag      8       12                      2     0      0   5
## 6 C6      yes     11 snag     10       16                      0     0      0   0
##    rocks soil litter dicot monocot     slope    aspect elevation regen_sum
## 1     10    0      0     0      30  9.644847 183.1099    31.018       194
## 2      5    0      0     0      25  9.774885 174.6427    32.059       205
## 3      5    0      0     0      10 10.201162 172.0026    37.471       147
## 4     40    0      0     0       5 14.868460 188.7625    56.675       131
## 5     25    0     70     0       0  1.957793 134.6838    19.341       174
## 6     60   30     10     0       0  3.302792 142.9560    21.166       275
##    regen_ha dead_volume_ha tot_regen avg_height seeder_nha seeder_avgh
```

```
## 1     17153      0.26507188        194       56.76         0         0.00
## 2     18125      0.07068583        205       98.96         0         0.00
## 3     12997      0.24127432        147      103.68       442        41.80
## 4     11582      0.54286721        131      110.91         0         0.00
## 5     15384     13.57168026        174       18.30     10521         4.39
## 6     24315    110.58406141        275       28.01      4420         4.14
##    resprout_nha resprout_avgh fac_nha fac_avgh
## 1          1149         61.78   16003    51.74
## 2          3625         96.88   14500   103.12
## 3           442         48.50   12113   142.70
## 4          2917        155.50    8665    66.32
## 5           795         30.33    4067    34.07
## 6          5747         57.34   14147    22.55
```

```r
# optional: remove temporary variables. Comment if you don't like the idea
# rm(list=setdiff(ls(), c("volume", "sites_df", "nplots")))
```

```r
#####Data transformation and distributions####################################
#try Tukey transformation ladder
t_height <- transformTukey(sites_df$avg_height)
```

```
##
##      lambda      W Shapiro.p.value
## 416   0.375 0.9287       5.479e-05
##
## if (lambda >  0){TRANS = x ^ lambda}
## if (lambda == 0){TRANS = log(x)}
## if (lambda <  0){TRANS = -1 * x ^ lambda}
```

```r
shapiro.test(t_height)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  t_height
## W = 0.92875, p-value = 5.479e-05
```

```r
t_dense <- transformTukey(sites_df$regen_ha)
```

```
##
##      lambda      W Shapiro.p.value
## 415    0.35 0.9627        0.007472
##
## if (lambda >  0){TRANS = x ^ lambda}
## if (lambda == 0){TRANS = log(x)}
## if (lambda <  0){TRANS = -1 * x ^ lambda}
```

```r
shapiro.test(t_dense)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  t_dense
## W = 0.96272, p-value = 0.007472
```

```r
#put independent variables into classes
                        ##SLOPE##
#split into classes -- flat, moderate, steep
slope_level <- vector(mode = 'character', length=nplots)
for (i in 1:length(sites_df$slope)){
```

```r
  if (sites_df$slope[i] <= 10){
    slope_level[i] <- 'flat'
  }
  else if(sites_df$slope[i] <= 20){
    slope_level[i] <- 'moderate'
  }
  else{
    slope_level[i] <- 'steep'
  }
}
sites_df$steepness <- factor(slope_level, levels=c("flat","moderate","steep"))


                              ##ASPECT##
#split into Ordinals (NE/SE/SW/NW)
ordinal <- vector(mode = 'character', length = nplots)
for (i in 1:length(sites_df$aspect)){
  if(sites_df$aspect[i]<=90){
    ordinal[i] <- 'NE'
  }
  else if(sites_df$aspect[i]<=180){
    ordinal[i] <- 'SE'
  }
  else if(sites_df$aspect[i]<=270){
    ordinal[i] <- 'SW'
  }
  else{
    ordinal[i] <- 'NW'
  }
}

sites_df$ordinals <- factor(ordinal, levels = c("NW","NE","SE","SW"))


                              ##DEADWOOD##
#split into volume classes -- low, medium, high
Qvol  <- quantile(volume, probs = c(1/3, 2/3))
for (i in 1:length(volume)){
    if(volume[i] <= Qvol[1]){
    volume[i] <- "Low"
    }
    else if(volume[i] <= Qvol[2]){
      volume[i] <- "Medium"
    }
    else if(volume[i] > Qvol[2])
    {
      volume[i] <- "High"
    }
}
sites_df$volume <- factor(volume, levels=c("Low","Medium","High"))


                              ##ELEVATION##
#split into classes-- low/Monfalcone, low/Slovenia, mid/Slovenia, high/Slovenia
elev_class <- vector(mode="character", length = nplots)
hist(sites_df$elevation)

slov_elev <- vector(mode="numeric")
slov_i <-1
for (i in 1:length(sites_df$elevation)){
  if(sites_df$elevation[i] > 200){
    slov_elev[slov_i] <- sites_df$elevation[i]
    slov_i <- slov_i + 1
```

```r
  }
 }
Qele <- quantile(slov_elev, probs = c(1/3, 2/3))
hist(slov_elev)

for(i in 1:length(sites_df$elevation)){
  if(sites_df$elevation[i] < 200){
    elev_class[i] <- "Sea"
  }
  else if (sites_df$elevation[i] <= Qele[1]){
    elev_class[i] <- "Low"
  }
  else if (sites_df$elevation[i] <= Qele[2]){
    elev_class[i] <- "Medium"
  }
  else{
    elev_class[i] <- "High"
  }
}
sites_df$elev_class <- factor(elev_class, levels=c("Sea", "Low", "Medium", "High"))

                        ##PHANE/CHAMAE/DICOT/MONOCOT##
#group all the plant cover classes together and into presence(>=5%)/absence(<5%)
#does not include litter cover
ground_cover <- vector(mode = 'character', length = nplots)
for (i in 1:length(sites_df$phane)){
  ground_cover[i] <- sites_df$phane[i] + sites_df$chamae[i] + sites_df$dicot[i]
  + sites_df$monocot[i]
  if(ground_cover[i] < 5){
    ground_cover[i] <- "Absent"
  }
  else{
    ground_cover[i] <- "Present"
  }
}
sites_df$ground<- ground_cover

                            ##ROCK COVER##
#divide into classes -- low(1), mid(2), high(3)
rock <- vector(mode = 'character', length = nplots)
for (i in 1:length(rock)){
  if(sites_df$rocks[i] < 35){
    rock[i] <- "Low"
  }
  else if(sites_df$rocks[i] < 60){
    rock[i] <- "Medium"
  }
  else{
    rock[i] <- "High"
  }
}
sites_df$rock_cover <- factor(rock, levels=c("Low","Medium","High"))

                            ##SOIL COVER##
#split into classes -- low(1), medium(2), high(3)
soils <- vector(mode='character', length = nplots)
for(i in 1:length(soils)){
   if(sites_df$soil[i] < 35){
    soils[i] <- 'Low'
  }
```

```r
  else if(sites_df$soil[i] < 60){
    soils[i] <- 'Medium'
  }
  else{
    soils[i] <- 'High'
  }
}
sites_df$soil_cover <- factor(soils, levels=c("Low","Medium","High"))

                              ##Litter(Detritus)##
hist(sites_df$litter)

lit <- vector(mode="character", length = nplots)
for(i in 1:length(lit)){
  if (sites_df$litter[i] == 0){
    lit[i] <- "None"
  }
  else if(sites_df$litter[i] < 50){
    lit[i] <- "Low"
  }
  else{
    lit[i] <- "High"
  }
}
sites_df$lit <- factor(lit, levels=c("None", "Low", "High"))

sites_df <- sites_df %>% select(ID, regen_ha, avg_height, seeder_nha, seeder_avgh,
                                resprout_nha, resprout_avgh, fac_nha, fac_avgh, steepness,
                                ordinals, volume, elev_class, ground, rock_cover,
                                soil_cover, lit)

###OUTPUTS#################################################################
                        ##Independent variable plots:##
ggplot(sites_df, aes(x= volume))+geom_bar()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Deadwood Volume")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())

ggplot(sites_df, aes(x=ground)) + geom_bar()+
  ggtitle("Vegetative Cover")+ xlab("Vegetative Cover >5%")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())

ords <- ggplot(sites_df, aes(x = ordinals)) + geom_bar()+
  ggtitle("Site Orientation") + xlab("Ordinals")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
elevs <- ggplot(sites_df, aes(x= elev_class)) + geom_bar() +
  scale_x_discrete(limits = c("Sea", "Low",
                              "Medium", "High"))+
  ggtitle("Elevation")+xlab("Elevation")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
slopes <- ggplot(sites_df, aes(x=steepness)) + geom_bar()+
  scale_x_discrete(limits = c("flat", "moderate", "steep")) + ggtitle("Slope") +
  xlab("Steepness")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggarrange(ords, elevs, slopes, ncol=3, nrow=1)

rocky <- ggplot(sites_df, aes(x = rock_cover))+geom_bar()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+ ggtitle("Rocky Cover")+
  xlab("Rocky Cover")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
soily <- ggplot(sites_df, aes(x= soil_cover))+geom_bar()+
```

```
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Mineral Soil Cover")+xlab("Soil Cover")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
litty<- ggplot(sites_df, aes(x = lit))+geom_bar()+
  scale_x_discrete(limits = c("None", "Low", "High"))+
  ggtitle("Leaf Litter Cover")+ xlab("Litter Cover")+theme_bw()+
  theme(panel.grid.major = element_blank(), panel.grid.minor = element_blank())
ggarrange(rocky, soily,litty, ncol=3, nrow=1)

##Density Kruskals##
##Slope##
dense.slope <- aov(t_dense~steepness, data=sites_df)
shapiro.test(dense.slope$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  dense.slope$residuals
## W = 0.98232, p-value = 0.2172

dense.slope <- kruskal.test(regen_ha~steepness, data=sites_df) #this is better
##Elevation##
dense.elev <- aov(t_dense~elev_class, data=sites_df)
shapiro.test(dense.elev$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  dense.elev$residuals
## W = 0.98417, p-value = 0.2956

dense.elev <- kruskal.test(regen_ha~elev_class, data=sites_df)
##Aspect##
dense.asp <- aov(t_dense~ordinals, data=sites_df)
shapiro.test(dense.asp$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  dense.asp$residuals
## W = 0.97705, p-value = 0.08707

dense.asp <- kruskal.test(regen_ha~ordinals, data=sites_df)
##Deadwood##
dense.wood <- aov(t_dense~volume, data=sites_df)
shapiro.test(dense.wood$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  dense.wood$residuals
## W = 0.97196, p-value = 0.0357

dense.wood <- kruskal.test(regen_ha~volume, data=sites_df)
##Veg cover##
dense.veg <- aov(t_dense~ground, data=sites_df)
shapiro.test(dense.veg$residuals) ##not normal, might need to do kruskal-wallis

##
##  Shapiro-Wilk normality test
##
```

```
## data:  dense.veg$residuals
## W = 0.95809, p-value = 0.003544

dense.veg <- kruskal.test(regen_ha~ground, data=sites_df)
##soils##
dense.soil <- aov(regen_ha~soil_cover, data=sites_df)
shapiro.test(dense.soil$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  dense.soil$residuals
## W = 0.74593, p-value = 1.163e-11

dense.soil <- kruskal.test(regen_ha~soil_cover, data=sites_df)
##rocks##
dense.rocks <- aov(t_dense~rock_cover, data=sites_df)
shapiro.test(dense.rocks$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  dense.rocks$residuals
## W = 0.97512, p-value = 0.06198

dense.rocks <- kruskal.test(regen_ha~rock_cover, data=sites_df)
##litter##
dense.litter <- aov(t_dense~lit, data=sites_df)
shapiro.test(dense.litter$residuals) #not normal, may need kruskal-wallis test

##
##  Shapiro-Wilk normality test
##
## data:  dense.litter$residuals
## W = 0.97002, p-value = 0.02553

dense.litter <- kruskal.test(regen_ha~lit, data=sites_df)


                            ##Height Kruskals##
##Slope##
height.slope <- aov(t_height~steepness, data=sites_df)
shapiro.test(height.slope$residuals) #not normal, use Kruskal

##
##  Shapiro-Wilk normality test
##
## data:  height.slope$residuals
## W = 0.91318, p-value = 8.312e-06

height.slope <- kruskal.test(avg_height~steepness, data=sites_df)
##Elevation##
height.elev <- aov(t_height~elev_class, data=sites_df)
shapiro.test(height.elev$residuals) #not normal, use kruskal

##
##  Shapiro-Wilk normality test
##
## data:  height.elev$residuals
## W = 0.97506, p-value = 0.06136
```

```r
height.elev <- kruskal.test(avg_height~elev_class, data=sites_df)
##Aspect##
height.asp <- aov(t_height~ordinals, data=sites_df)
shapiro.test(height.asp$residuals)#not normal, use kruskal

##
##  Shapiro-Wilk normality test
##
## data:  height.asp$residuals
## W = 0.93849, p-value = 0.000198

height.asp <- kruskal.test(avg_height~ordinals, data=sites_df)
##Deadwood##
height.wood <- aov(t_height~volume, data=sites_df)
shapiro.test(height.wood$residuals)#not normal

##
##  Shapiro-Wilk normality test
##
## data:  height.wood$residuals
## W = 0.95622, p-value = 0.002637

height.wood <- kruskal.test(avg_height~volume, data=sites_df)
##Veg cover##
height.veg <- aov(t_height~ground, data=sites_df)
shapiro.test(height.veg$residuals) ##not normal, use kruskal

##
##  Shapiro-Wilk normality test
##
## data:  height.veg$residuals
## W = 0.93778, p-value = 0.0001797

height.veg <- kruskal.test(avg_height~ground, data=sites_df)
##soils##
height.soil <- aov(t_height~soil_cover, data=sites_df)
shapiro.test(height.soil$residuals) #not normal

##
##  Shapiro-Wilk normality test
##
## data:  height.soil$residuals
## W = 0.97011, p-value = 0.02594

height.soil <- kruskal.test(avg_height~soil_cover, data=sites_df)
##rocks##
height.rocks <- aov(t_height~rock_cover, data=sites_df)
shapiro.test(height.rocks$residuals) #not normal

##
##  Shapiro-Wilk normality test
##
## data:  height.rocks$residuals
## W = 0.93905, p-value = 0.0002138

height.rocks <- kruskal.test(avg_height~rock_cover, data=sites_df)
##litter##
height.litter <- aov(t_height~lit, data=sites_df)
shapiro.test(height.litter$residuals) #not normal, may need kruskal-wallis test

##
##  Shapiro-Wilk normality test
```

```
##
## data:  height.litter$residuals
## W = 0.89739, p-value = 1.462e-06

height.litter <- kruskal.test(avg_height~lit, data=sites_df)
```

##Seeder Kruskals##
```
#density
seed.slope <- kruskal.test(seeder_nha~steepness, data=sites_df) #Slope
seed.elev <- kruskal.test(seeder_nha~elev_class, data=sites_df) #elevation
seed.asp <- kruskal.test(seeder_nha~ordinals, data=sites_df) #aspect
seed.wood <- kruskal.test(seeder_nha~volume, data=sites_df) #deadwood
seed.veg <- kruskal.test(seeder_nha~ground, data=sites_df) #veg cover
seed.soil <- kruskal.test(seeder_nha~soil_cover, data=sites_df) #soil
seed.rock <- kruskal.test(seeder_nha~rock_cover, data=sites_df) #rocks
seed.lit <- kruskal.test(seeder_nha~lit, data=sites_df) #litter
#height
seed.h.slope <- kruskal.test(seeder_avgh~steepness, data=sites_df) #Slope
seed.h.elev <- kruskal.test(seeder_avgh~elev_class, data=sites_df) #elevation
seed.h.asp <- kruskal.test(seeder_avgh~ordinals, data=sites_df) #aspect
seed.h.wood <- kruskal.test(seeder_avgh~volume, data=sites_df) #deadwood
seed.h.veg <- kruskal.test(seeder_avgh~ground, data=sites_df) #veg cover
seed.h.soil <- kruskal.test(seeder_avgh~soil_cover, data=sites_df) #soil
seed.h.rock <- kruskal.test(seeder_avgh~rock_cover, data=sites_df) #rocks
seed.h.lit <- kruskal.test(seeder_avgh~lit, data=sites_df) #litter
```

##Resprout kruskals##
```
#density
resprout.slope <- kruskal.test(resprout_nha~steepness, data=sites_df) #Slope
resprout.elev <- kruskal.test(resprout_nha~elev_class, data=sites_df) #elevation
resprout.asp <- kruskal.test(resprout_nha~ordinals, data=sites_df) #aspect
resprout.wood <- kruskal.test(resprout_nha~volume, data=sites_df) #deadwood
resprout.veg <- kruskal.test(resprout_nha~ground, data=sites_df) #veg cover
resprout.soil <- kruskal.test(resprout_nha~soil_cover, data=sites_df) #soil
resprout.rock <- kruskal.test(resprout_nha~rock_cover, data=sites_df) #rocks
resprout.lit <- kruskal.test(resprout_nha~lit, data=sites_df) #litter
#height
resprout.h.slope <- kruskal.test(resprout_nha~steepness, data=sites_df) #Slope
resprout.h.elev <- kruskal.test(resprout_nha~elev_class, data=sites_df) #elevation
resprout.h.asp <- kruskal.test(resprout_nha~ordinals, data=sites_df) #aspect
resprout.h.wood <- kruskal.test(resprout_nha~volume, data=sites_df) #deadwood
resprout.h.veg <- kruskal.test(resprout_nha~ground, data=sites_df) #veg cover
resprout.h.soil <- kruskal.test(resprout_nha~soil_cover, data=sites_df) #soil
resprout.h.rock <- kruskal.test(resprout_nha~rock_cover, data=sites_df) #rocks
resprout.h.lit <- kruskal.test(resprout_nha~lit, data=sites_df) #litter
```

##facultative Kruskals###
```
#density
fac.slope <- kruskal.test(fac_nha~steepness, data=sites_df) #Slope
fac.elev <- kruskal.test(fac_nha~elev_class, data=sites_df) #elevation
fac.asp <- kruskal.test(fac_nha~ordinals, data=sites_df) #aspect
fac.wood <- kruskal.test(fac_nha~volume, data=sites_df) #deadwood
fac.veg <- kruskal.test(fac_nha~ground, data=sites_df) #veg cover
fac.soil <- kruskal.test(fac_nha~soil_cover, data=sites_df) #soil
fac.rock <- kruskal.test(fac_nha~rock_cover, data=sites_df) #rocks
fac.lit <- kruskal.test(fac_nha~lit, data=sites_df) #litter
#height
fac.h.slope <- kruskal.test(fac_avgh~steepness, data=sites_df) #Slope
fac.h.elev <- kruskal.test(fac_avgh~elev_class, data=sites_df) #elevation
fac.h.asp <- kruskal.test(fac_avgh~ordinals, data=sites_df) #aspect
```

```r
fac.h.wood <- kruskal.test(fac_avgh~volume, data=sites_df) #deadwood
fac.h.veg <- kruskal.test(fac_avgh~ground, data=sites_df) #veg cover
fac.h.soil <- kruskal.test(fac_avgh~soil_cover, data=sites_df) #soil
fac.h.rock <- kruskal.test(fac_avgh~rock_cover, data=sites_df) #rocks
fac.h.lit <- kruskal.test(fac_avgh~lit, data=sites_df) #litter


par(mfrow=c(1,2))
hist(sites_df$seeder_nha, main = "Obligate Seeder Density",
     xlab = "Seeder Density (n/ha)", ylab="Site Count")
hist(sites_df$seeder_avgh, main = "Obligate Seeder Performance",
     xlab = "Seeder Performance (cm)", ylab="Site Count")


par(mfrow=c(1,1))
summary(sites_df$seeder_nha)


##    Min. 1st Qu. Median    Mean 3rd Qu.     Max.
##     0.0     0.0    0.0   416.5     0.0 17330.0


summary(sites_df$seeder_avgh)


##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.7506  0.0000 41.8000


par(mfrow=c(1,2))
hist(sites_df$fac_nha, main = "Facultative Seeder Density",
     xlab = "Facultative Seeder Density (n/ha)", ylab="Site Count")
hist(sites_df$fac_avgh, main = "Seeder Performance",
     xlab = "Facultative Seeder Performance (cm)", ylab="Site Count")


par(mfrow=c(1,1))
summary(sites_df$fac_nha)


##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0     972    3359    3890   36605


summary(sites_df$fac_avgh)


##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    6.00   11.19   10.22  142.70


##Dunns##
##veg categories for wilcox test
veg.bin <- vector(mode='numeric', length=97)
for(i in 1:length(sites_df$ground)){
  if(sites_df$ground[i] == "Absent"){
    veg.bin[i] <- 0
  }
  else{
    veg.bin[i] <- 1
  }
}
                    ##Dunn tests -> CLD boxplots##
              #Site totals first#
#Slope
slope.dunn <- dunnTest(regen_ha~steepness, data = sites_df, method='holm')$res
slope.regen.cld <- cldList(P.adj~Comparison, data = slope.dunn)
slope.h.dunn <- dunnTest(avg_height~steepness, data = sites_df,
                         method='holm')$res
clds <- cldList(P.adj~Comparison, data = slope.h.dunn)
##add to the boxplot
slope_meds <- sites_df %>% group_by(steepness) %>% dplyr::summarize(
```

```r
    Median = median(regen_ha, na.rm = TRUE), quant =
      quantile(regen_ha, probs = 0.75)) %>% arrange(desc(Median))
slope_meds$letter <- slope.regen.cld$MonoLetter
d.slope <- ggplot(sites_df, aes(y= regen_ha, x= steepness))+geom_boxplot()+
  scale_x_discrete(limits = c("flat", "moderate", "steep"))+
  ggtitle("Regeneration Density")+
  labs(x="Slope", y="Regeneration Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=slope_meds, aes(label = letter, x = steepness, y = quant),
            vjust = -1, hjust = -1)
slope_meds <- sites_df %>% group_by(steepness) %>% dplyr::summarize(
  Median = median(avg_height, na.rm = TRUE), quant =
    quantile(avg_height, probs = 0.75)) %>% arrange(desc(Median))
slope_meds$letter <- clds$MonoLetter
d.h.slope <- ggplot(sites_df, aes(y= avg_height, x= steepness))+geom_boxplot()+
  scale_x_discrete(limits = c("flat", "moderate", "steep"))+
  ggtitle("Regeneration Performance")+
  labs(x="Slope", y="Regeneration Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=slope_meds, aes(label = letter, x = steepness, y = quant),
            vjust = -1, hjust = -1)
ggarrange(d.slope, d.h.slope, nrow=1, ncol=2)

#elevation
el.dunn <- dunnTest(regen_ha~elev_class, data = sites_df, method='holm')$res
el.order <- c("Sea - Low", "Low - Medium", "Medium - High", "Sea - High",
              "Low - High", "Sea - Medium")
el.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                        "Sea - High", "Sea - Low", "Sea - Medium")
el.dunn$Comparison <- factor(el.dunn$Comparison, levels =  el.order)
el.dunn<- el.dunn[order(el.dunn$Comparison),]
cld1 <- cldList(P.adj~factor(Comparison, levels = c("Sea", "Low", "Medium",
                                                    "High")) , data = el.dunn)
el.h.dunn <- dunnTest(avg_height~elev_class, data = sites_df, method='holm')$res
el.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                          "Sea - High", "Sea - Low", "Sea - Medium")
el.h.dunn$Comparison <- factor(el.h.dunn$Comparison, levels =  el.order)
el.h.dunn<- el.h.dunn[order(el.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = el.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(
  Median = median(regen_ha, na.rm = TRUE), quant =
    quantile(regen_ha, probs = 0.75)) %>% arrange(desc(Median))
  meds$letter <- cld1$MonoLetter
d.el <- ggplot(sites_df, aes(y= regen_ha, x= elev_class))+geom_boxplot()+
scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
ggtitle("Regeneration Density")+
labs(x="Elevation", y="Regeneration Density (n/ha)")+
theme_bw()+ theme(panel.grid.major = element_blank(),
                  panel.grid.minor=element_blank())+
geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
          vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(
  Median = median(avg_height, na.rm = TRUE),
  quant = quantile(avg_height, probs = 0.75)) %>% arrange(desc(Median))
meds$letter <- cld2$MonoLetter
d.h.el <- ggplot(sites_df, aes(y= avg_height, x= elev_class))+geom_boxplot()+
  scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Regeneration Performance")+
```

```r
    labs(x="Elevation", y="Regeneration Performance (cm)")+
    theme_bw()+ theme(panel.grid.major = element_blank(),
                      panel.grid.minor=element_blank())+
    geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
              vjust = -0.5, hjust = -0.5)
ggarrange(d.el, d.h.el, nrow=1, ncol=2)

#Veg Cover

veg.dunn <- wilcox.test(veg.bin, sites_df$fac_nha, correct=FALSE, exact=FALSE)
##add to the boxplot
d.veg <- ggplot(sites_df, aes(y= regen_ha, x= ground))+geom_boxplot()+
    scale_x_discrete(limits = c("Absent", "Present"))+
    ggtitle("Regeneration Density")+
    labs(x="Vegetative Cover >5%", y="Regeneration Density (n/ha)")+
    theme_bw()+ theme(panel.grid.major = element_blank(),
                      panel.grid.minor=element_blank())
d.h.veg <- ggplot(sites_df, aes(y= avg_height, x= ground))+geom_boxplot()+
    scale_x_discrete(limits = c("Absent", "Present"))+
    ggtitle("Regeneration Performance")+
    labs(x="Vegetative Cover >5%", y="Regeneration Performance (cm)")+
    theme_bw()+ theme(panel.grid.major = element_blank(),
                      panel.grid.minor=element_blank())
ggarrange(d.veg, d.h.veg, nrow = 1, ncol = 2)

#Soil Cover

soil.dunn <- dunnTest(regen_ha~soil_cover, data = sites_df, method='holm')$res
soil.order <- c("Low - High", "Medium - High", "Low - Medium")
soil.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
soil.dunn$Comparison <- factor(soil.dunn$Comparison, levels =  soil.order)
soil.dunn<- soil.dunn[order(soil.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison, data = soil.dunn)
soil.h.dunn <- dunnTest(avg_height~soil_cover, data = sites_df,
                        method='holm')$res
soil.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
soil.h.dunn$Comparison <- factor(soil.h.dunn$Comparison, levels =  soil.order)
soil.h.dunn<- soil.h.dunn[order(soil.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = soil.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(soil_cover) %>% dplyr::summarize(
    Median = median(regen_ha, na.rm = TRUE),
    quant = quantile(regen_ha, probs = 0.75)) %>% arrange(desc(Median))
meds$letter <- cld1$MonoLetter
d.soil <- ggplot(sites_df, aes(y= regen_ha, x= soil_cover))+geom_boxplot()+
    scale_x_discrete(limits = c("Low", "Medium", "High"))+
    ggtitle("Regeneration Density")+
    labs(x="Mineral Soil Cover", y="Regeneration Density (n/ha)")+
    theme_bw()+ theme(panel.grid.major = element_blank(),
                      panel.grid.minor=element_blank())+
    geom_text(data=meds, aes(label = letter, x = soil_cover, y = quant),
              vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(soil_cover) %>% dplyr::summarize(
    Median = median(avg_height, na.rm = TRUE),
    quant = quantile(avg_height, probs = 0.75)) %>% arrange(desc(Median))
meds$letter <- cld2$MonoLetter
d.h.soil <- ggplot(sites_df, aes(y= avg_height, x= soil_cover))+geom_boxplot()+
    scale_x_discrete(limits = c("Low", "Medium", "High"))+
    ggtitle("Regeneration Performance")+
    labs(x="Mineral Soil Cover", y="Regeneration Performance (cm)")+
    theme_bw()+ theme(panel.grid.major = element_blank(),
```

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                        panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = soil_cover, y = quant),
                vjust = -0.5, hjust = -0.5)
ggarrange(d.soil, d.h.soil, nrow=1, ncol=2)

#Litter
lit.dunn <- dunnTest(regen_ha~lit, data = sites_df, method='holm')$res
lit.order <- c("None - Low", "Low - High", "None - High")
lit.dunn$Comparison <- c("Low - High", "None - High", "None - Low")
lit.dunn$Comparison <- factor(lit.dunn$Comparison, levels =  lit.order)
lit.dunn<- lit.dunn[order(lit.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = lit.dunn)
lit.h.dunn <- dunnTest(avg_height~lit, data = sites_df, method='holm')$res
lit.h.dunn$Comparison <- c("Low - High", "None - High", "None - Low")
lit.h.dunn$Comparison <- factor(lit.h.dunn$Comparison, levels =  lit.order)
lit.h.dunn<- lit.h.dunn[order(lit.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = lit.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(lit) %>% dplyr::summarize(
  Median = median(regen_ha, na.rm = TRUE),
  quant = quantile(regen_ha, probs = 0.75))
meds$letter <- cld1$MonoLetter
d.lit <- ggplot(sites_df, aes(y= regen_ha, x= lit))+geom_boxplot()+
  scale_x_discrete(limits = c("None", "Low", "High"))+
  ggtitle("Regeneration Density")+
  labs(x="Leaf Litter Cover", y="Regeneration Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = lit, y = quant),
                vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(lit) %>% dplyr::summarize(
  Median = median(avg_height, na.rm = TRUE),
  quant = quantile(avg_height, probs = 0.75))
meds$letter <- cld2$MonoLetter
d.h.lit <- ggplot(sites_df, aes(y= avg_height, x= lit))+geom_boxplot()+
  scale_x_discrete(limits = c("None", "Low", "High"))+
  ggtitle("Regeneration Performance")+
  labs(x="Leaf Litter Cover", y="Regeneration Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = lit, y = quant),
                vjust = -0.5, hjust = -0.5)
ggarrange(d.lit, d.h.lit, nrow=1, ncol=2)

#Deadwood(n/ha) and Rocks(h)
vol.dunn <- dunnTest(regen_ha~volume, data = sites_df, method='holm')$res
vol.order <- c("Low - High", "Medium - High", "Low - Medium")
vol.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
vol.dunn$Comparison <- factor(vol.dunn$Comparison, levels =  vol.order)
vol.dunn<- vol.dunn[order(vol.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = vol.dunn)
rock.h.dunn <- dunnTest(avg_height~rock_cover, data = sites_df,
                        method='holm')$res
rock.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
rock.h.dunn$Comparison <- factor(rock.h.dunn$Comparison, levels =  vol.order)
rock.h.dunn<- rock.h.dunn[order(rock.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = rock.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(volume) %>% dplyr::summarize(
  Median = median(regen_ha, na.rm = TRUE),
  quant = quantile(regen_ha, probs = 0.75))
```

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meds$letter <- cld1$MonoLetter
d.vol <- ggplot(sites_df, aes(y= regen_ha, x= volume))+geom_boxplot()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Regeneration Density")+
  labs(x="Deadwood Volume", y="Regeneration Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = volume, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(rock_cover) %>% dplyr::summarize(
  Median = median(avg_height, na.rm = TRUE),
  quant = quantile(avg_height, probs = 0.75))
meds$letter <- cld2$MonoLetter
d.h.rock <- ggplot(sites_df, aes(y= avg_height, x= rock_cover))+geom_boxplot()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Regeneration Performance")+
  labs(x="Rocky Cover", y="Regeneration Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = rock_cover, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(d.vol, d.h.rock, nrow=1, ncol=2)

#for the regen strategy groups
#seeder elev
seed.el.dunn <- dunnTest(seeder_nha~elev_class, data = sites_df,
                         method='holm')$res
seed.el.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                             "Sea - High", "Sea - Low", "Sea - Medium")
seed.el.dunn$Comparison <- factor(seed.el.dunn$Comparison, levels =  el.order)
seed.el.dunn<- seed.el.dunn[order(seed.el.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = seed.el.dunn)
seed.el.h <- dunnTest(seeder_avgh~elev_class, data = sites_df, method='holm')$res
seed.el.h$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                          "Sea - High", "Sea - Low", "Sea - Medium")
seed.el.h$Comparison <- factor(seed.el.h$Comparison, levels =  el.order)
seed.el.h<- seed.el.h[order(seed.el.h$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = seed.el.h)
##add to the boxplot
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(
  Median = median(seeder_nha, na.rm = TRUE),
  quant = quantile(seeder_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
d.seed.el <- ggplot(sites_df, aes(y= seeder_nha, x= elev_class))+geom_boxplot()+
  scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Obligate Seeder Density")+
  labs(x="Elevation", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(
  Median = median(seeder_avgh, na.rm = TRUE),
  quant = quantile(seeder_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
el.h.seed <- ggplot(sites_df, aes(y= seeder_avgh, x= elev_class))+geom_boxplot()+
  scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Obligate Seeder Performance")+
  labs(x="Elevation", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
```

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  geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(d.seed.el, el.h.seed, nrow=1, ncol=2)


#Resprouters
                                                #slope
sprout.slope.dunn <- dunnTest(resprout_nha~steepness,
                              data = sites_df, method='holm')$res
cld1 <- cldList(P.adj~Comparison, data = sprout.slope.dunn)
sprout.slope.h.dunn <- dunnTest(resprout_avgh~steepness,
                                data = sites_df, method='holm')$res
cld2 <- cldList(P.adj~Comparison, data = sprout.slope.h.dunn)
#boxplot
meds <- sites_df %>% group_by(steepness) %>% dplyr::summarize(
  Median = median(resprout_nha, na.rm = TRUE),
  quant = quantile(resprout_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
d.sprout.slope <- ggplot(sites_df, aes(y= resprout_nha, x= steepness))+
  geom_boxplot()+ scale_x_discrete(limits = c("flat", "moderate", "steep"))+
  ggtitle("Obligate Resprouter Density")+
  labs(x="Slope", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = steepness, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(steepness) %>% dplyr::summarize(
  Median = median(resprout_avgh, na.rm = TRUE),
  quant = quantile(resprout_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
slope.h.sprout <- ggplot(sites_df, aes(y= resprout_avgh, x= steepness))+
  geom_boxplot()+ scale_x_discrete(limits = c("flat", "moderate", "steep"))+
  ggtitle("Obligate Resprouter Performance")+
  labs(x="Slope", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = steepness, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(d.sprout.slope, slope.h.sprout, nrow=1, ncol=2)


#Elevation
sprout.el.dunn <- dunnTest(resprout_nha~elev_class,
                           data = sites_df, method='holm')$res
sprout.el.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                               "Sea - High", "Sea - Low", "Sea - Medium")
sprout.el.dunn$Comparison <- factor(sprout.el.dunn$Comparison,
                                    levels =  el.order)
sprout.el.dunn<- sprout.el.dunn[order(sprout.el.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = sprout.el.dunn)
sprout.el.h.dunn <- dunnTest(resprout_avgh~elev_class,
                             data = sites_df, method='holm')$res
sprout.el.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                                 "Sea - High", "Sea - Low", "Sea - Medium")
sprout.el.h.dunn$Comparison <- factor(sprout.el.h.dunn$Comparison,
                                      levels =  el.order)
sprout.el.h.dunn<- sprout.el.h.dunn[order(sprout.el.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = sprout.el.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(Median = median(
  resprout_nha, na.rm = TRUE), quant = quantile(resprout_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
sprout.d.el <- ggplot(sites_df, aes(y= resprout_nha, x= elev_class))+
```

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  geom_boxplot()+ scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Obligate Resprouter Density")+
  labs(x="Elevation", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(Median = median(
  resprout_avgh, na.rm = TRUE), quant = quantile(resprout_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
sprout.h.el <- ggplot(sites_df, aes(y= resprout_avgh, x= elev_class))+
  geom_boxplot()+ scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Obligate Resprouter Performance")+
  labs(x="Elevation", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(sprout.d.el, sprout.h.el, nrow=1, ncol=2)

#deadwood (n/ha) and veg cover(h)
sprout.vol.dunn <- dunnTest(resprout_nha~volume, data = sites_df,
                            method='holm')$res
vol.order <- c("Low - High", "Medium - High", "Low - Medium")
sprout.vol.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
sprout.vol.dunn$Comparison <- factor(sprout.vol.dunn$Comparison,
                                     levels =  vol.order)
sprout.vol.dunn<- sprout.vol.dunn[order(sprout.vol.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = sprout.vol.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(volume) %>% dplyr::summarize(Median = median(
  resprout_nha, na.rm = TRUE), quant = quantile(resprout_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
sprout.d.vol <- ggplot(sites_df, aes(y= resprout_nha, x= volume))+geom_boxplot()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Obligate Resprouter Density")+
  labs(x="Deadwood Volume", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = volume, y = quant),
            vjust = -1, hjust = -0.5)
sprout.h.veg <- ggplot(sites_df, aes(y= resprout_avgh, x= ground))+geom_boxplot()+
  scale_x_discrete(limits = c("Absent", "Present"))+
  ggtitle("Obligate Resprouter Performance")+
  labs(x="Vegetation Cover >5%", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())
ggarrange(sprout.d.vol, sprout.h.veg, nrow=1, ncol=2)

#litter
sprout.lit.dunn <- dunnTest(resprout_nha~lit, data = sites_df, method='holm')$res
sprout.lit.order <- c("None - Low", "Low - High", "None - High")
sprout.lit.dunn$Comparison <- c("Low - High", "None - High", "None - Low")
sprout.lit.dunn$Comparison <- factor(sprout.lit.dunn$Comparison,
                                     levels =  lit.order)
sprout.lit.dunn<- sprout.lit.dunn[order(sprout.lit.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = sprout.lit.dunn)
sprout.lit.h.dunn <- dunnTest(resprout_avgh~lit, data = sites_df,
                              method='holm')$res
sprout.lit.h.dunn$Comparison <- c("Low - High", "None - High", "None - Low")
sprout.lit.h.dunn$Comparison <- factor(sprout.lit.h.dunn$Comparison,
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                                        levels =  lit.order)
sprout.lit.h.dunn<- sprout.lit.h.dunn[order(sprout.lit.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = sprout.lit.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(lit) %>% dplyr::summarize(Median = median(
  resprout_nha, na.rm = TRUE), quant = quantile(resprout_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
sprout.d.lit <- ggplot(sites_df, aes(y= resprout_nha, x= lit))+geom_boxplot()+
  scale_x_discrete(limits = c("None", "Low", "High"))+
  ggtitle("Obligate Resprouter Density")+
  labs(x="Leaf Litter Cover", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = lit, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(lit) %>% dplyr::summarize(Median = median(
  resprout_avgh, na.rm = TRUE), quant = quantile(resprout_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
sprout.h.lit <- ggplot(sites_df, aes(y= resprout_avgh, x= lit))+geom_boxplot()+
  scale_x_discrete(limits = c("None", "Low", "High"))+
  ggtitle("Obligate Resprouter Performance")+
  labs(x="Leaf Litter Cover", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = lit, y = quant),
            vjust = -0.5, hjust = -0.5)


ggarrange(sprout.d.lit, sprout.h.lit, nrow=1, ncol=2)


#soil
sprout.soil.dunn <- dunnTest(resprout_nha~soil_cover, data = sites_df,
                             method='holm')$res
sprout.soil.order <- c("Low - High", "Medium - High", "Low - Medium")
sprout.soil.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
sprout.soil.dunn$Comparison <- factor(sprout.soil.dunn$Comparison,
                                      levels =  soil.order)
sprout.soil.dunn<- sprout.soil.dunn[order(sprout.soil.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison, data = sprout.soil.dunn)
sprout.soil.h.dunn <- dunnTest(resprout_nha~soil_cover, data = sites_df,
                               method='holm')$res
sprout.soil.h.dunn$Comparison <- c("Low - High", "Medium - High",
                                   "Low - Medium")
sprout.soil.h.dunn$Comparison <- factor(sprout.soil.h.dunn$Comparison,
                                        levels =  soil.order)
sprout.soil.h.dunn<- sprout.soil.h.dunn[order(sprout.soil.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = sprout.soil.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(soil_cover) %>% dplyr::summarize(Median = median(
  resprout_nha, na.rm = TRUE), quant = quantile(resprout_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
sprout.d.soil <- ggplot(sites_df, aes(y= resprout_nha, x= soil_cover))+
  geom_boxplot()+ scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Obligate Resprouter Density")+
  labs(x="Mineral Soil Cover", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = soil_cover, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(soil_cover) %>% dplyr::summarize(Median = median(
  resprout_nha, na.rm = TRUE), quant = quantile(resprout_nha, probs = 0.75))
meds$letter <- cld2$MonoLetter
```

```
sprout.h.soil <- ggplot(sites_df, aes(y= resprout_nha, x= soil_cover))+
  geom_boxplot()+ scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Obligate Resprouter Performance")+
  labs(x="Mineral Soil Cover", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = soil_cover, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(sprout.d.soil, sprout.h.soil, nrow=1, ncol=2)

##Faclutative Seeders
fac.slope.dunn <- dunnTest(fac_nha~steepness, data = sites_df, method='holm')$res
cld1 <- cldList(P.adj~Comparison, data = fac.slope.dunn)
fac.slope.h.dunn <- dunnTest(fac_avgh~steepness, data = sites_df, method='holm')$res
cld2 <- cldList(P.adj~Comparison, data = fac.slope.h.dunn)
#boxplot
meds <- sites_df %>% group_by(steepness) %>% dplyr::summarize(Median = median(
  fac_nha, na.rm = TRUE), quant = quantile(fac_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
d.fac.slope <- ggplot(sites_df, aes(y= fac_nha, x= steepness))+geom_boxplot()+
  scale_x_discrete(limits = c("flat", "moderate", "steep"))+
  ggtitle("Facultative Seeder Density")+
  labs(x="Slope", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = steepness, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(steepness) %>% dplyr::summarize(Median = median(
  fac_avgh, na.rm = TRUE), quant = quantile(fac_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
slope.h.fac <- ggplot(sites_df, aes(y= fac_avgh, x= steepness))+geom_boxplot()+
  scale_x_discrete(limits = c("flat", "moderate", "steep"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Slope", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = steepness, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(d.fac.slope, slope.h.fac, nrow=1, ncol=2)

#Elevation
fac.el.dunn <- dunnTest(fac_nha~elev_class, data = sites_df, method='holm')$res
fac.el.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                            "Sea - High", "Sea - Low", "Sea - Medium")
fac.el.dunn$Comparison <- factor(fac.el.dunn$Comparison, levels =  el.order)
fac.el.dunn<- fac.el.dunn[order(fac.el.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison , data = fac.el.dunn)
fac.el.h.dunn <- dunnTest(fac_avgh~elev_class, data = sites_df, method='holm')$res
fac.el.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium",
                              "Sea - High", "Sea - Low", "Sea - Medium")
fac.el.h.dunn$Comparison <- factor(fac.el.h.dunn$Comparison, levels =  el.order)
fac.el.h.dunn<- fac.el.h.dunn[order(fac.el.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = fac.el.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(Median = median(
  fac_nha, na.rm = TRUE), quant = quantile(fac_nha, probs = 0.75))
meds$letter <- cld1$MonoLetter
fac.d.el <- ggplot(sites_df, aes(y= fac_nha, x= elev_class))+geom_boxplot()+
  scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Facultative Seeder Density")+
  labs(x="Elevation", y="Density (n/ha)")+
```

```r
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(elev_class) %>% dplyr::summarize(Median = median(
  fac_avgh, na.rm = TRUE), quant = quantile(fac_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
fac.h.el <- ggplot(sites_df, aes(y= fac_avgh, x= elev_class))+geom_boxplot()+
  scale_x_discrete(limits = c("Sea", "Low", "Medium", "High"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Elevation", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = elev_class, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(fac.d.el, fac.h.el, nrow=1, ncol=2)

#Aspect
fac.asp.dunn <- dunnTest(fac_nha~ordinals, data = sites_df, method='holm')$res
fac.asp.dunn$Comparison <- c("NW - NE", "NE - SE", "NW - SE", "SW - NE",
                             "SW - NW", "SW - SE")
cld1 <- cldList(P.adj~Comparison , data = fac.asp.dunn)
fac.asp.h.dunn <- dunnTest(fac_avgh~ordinals, data = sites_df, method='holm')$res
fac.asp.h.dunn$Comparison <- c("NW - NE", "NE - SE", "NW - SE", "SW - NE",
                               "SW - NW", "SW - SE")
cld2 <- cldList(P.adj~Comparison, data = fac.asp.h.dunn)
##add to the boxplot
meds <- sites_df %>% group_by(ordinals) %>% dplyr::summarize(Median = median(
  fac_nha, na.rm = TRUE), quant = quantile(fac_nha, probs = 0.75))
asp.ord <- c("NW", "NE", "SE", "SW")
cld1$Group <- factor(cld1$Group, levels = asp.ord)
cld1 <- cld1[order(cld1$Group),]
meds$letter <- cld1$MonoLetter
fac.d.asp <- ggplot(sites_df, aes(y= fac_nha, x= ordinals))+geom_boxplot()+
  scale_x_discrete(limits = c("NW", "NE", "SE", "SW"))+
  ggtitle("Facultative Seeder Density")+
  labs(x="Plot Ordinal", y="Density (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = ordinals, y = quant),
            vjust = -1, hjust = -0.5)
meds <- sites_df %>% group_by(ordinals) %>% dplyr::summarize(Median = median(
  fac_avgh, na.rm = TRUE), quant = quantile(fac_avgh, probs = 0.75))
cld2$Group <- factor(cld2$Group, levels = asp.ord)
cld2 <- cld2[order(cld2$Group),]
meds$letter <- cld2$MonoLetter
fac.h.asp <- ggplot(sites_df, aes(y= fac_avgh, x= ordinals))+geom_boxplot()+
  scale_x_discrete(limits = c("NW", "NE", "SE", "SW"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Plot Ordinal", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = ordinals, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(fac.d.asp, fac.h.asp, nrow=1, ncol=2)

fac.veg.dunn <- wilcox.test(veg.bin, sites_df$fac_nha, correct=FALSE, exact=FALSE)
fac.veg.h.dunn <- wilcox.test(veg.bin, sites_df$fac_avgh, correct=FALSE,
                              exact=FALSE)
fac.d.veg <- ggplot(sites_df, aes(y= fac_nha, x= ground))+geom_boxplot()+
  scale_x_discrete(limits = c("Absent", "Present"))+
```

```r
  ggtitle("Facultative Seeder Density")+
  labs(x="Vegetative Cover >5%", y="Desnity (n/ha)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())
fac.h.veg <- ggplot(sites_df, aes(y= fac_avgh, x= ground))+geom_boxplot()+
  scale_x_discrete(limits = c("Absent", "Present"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Vegetative Cover >5%", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())
ggarrange(fac.d.veg, fac.h.veg, ncol=2, nrow=1)


##Fac rocks
fac.rock.h.dunn <- dunnTest(fac_avgh~rock_cover, data = sites_df,
                            method='holm')$res
fac.rock.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
fac.rock.h.dunn$Comparison <- factor(fac.rock.h.dunn$Comparison,
                                     levels =  vol.order)
fac.rock.h.dunn<- fac.rock.h.dunn[order(fac.rock.h.dunn$Comparison),]
cld1 <- cldList(P.adj~Comparison, data = fac.rock.h.dunn)
meds <- sites_df %>% group_by(rock_cover) %>% dplyr::summarize(Median = median(
  fac_avgh, na.rm = TRUE), quant = quantile(fac_avgh, probs = 0.75))
meds$letter <- cld1$MonoLetter
fac.h.rock <- ggplot(sites_df, aes(y= fac_avgh, x= rock_cover))+geom_boxplot()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Rocky Cover", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = rock_cover, y = quant),
            vjust = -0.5, hjust = -0.5)
#soil
fac.soil.h.dunn <- dunnTest(fac_avgh~soil_cover, data = sites_df, method='holm')$res
fac.soil.h.dunn$Comparison <- c("Low - High", "Medium - High", "Low - Medium")
fac.soil.h.dunn$Comparison <- factor(fac.soil.h.dunn$Comparison,
                                     levels =  vol.order)
fac.soil.h.dunn<- fac.soil.h.dunn[order(fac.soil.h.dunn$Comparison),]
cld2 <- cldList(P.adj~Comparison, data = fac.soil.h.dunn)
meds <- sites_df %>% group_by(soil_cover) %>% dplyr::summarize(Median = median(
  fac_avgh, na.rm = TRUE), quant = quantile(fac_avgh, probs = 0.75))
meds$letter <- cld2$MonoLetter
fac.h.soil <- ggplot(sites_df, aes(y= fac_avgh, x= soil_cover))+geom_boxplot()+
  scale_x_discrete(limits = c("Low", "Medium", "High"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Mineral Soil Cover", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = soil_cover, y = quant),
            vjust = -0.5, hjust = -0.5)


#litter
fac.lit.h.dunn <- dunnTest(fac_avgh~lit, data = sites_df, method='holm')$res
fac.lit.h.dunn$Comparison <- c("Low - High", "None - High", "None - Low")
fac.lit.h.dunn$Comparison <- factor(fac.lit.h.dunn$Comparison,
                                    levels =  lit.order)
fac.lit.h.dunn<- fac.lit.h.dunn[order(fac.lit.h.dunn$Comparison),]
cld3 <- cldList(P.adj~Comparison, data = fac.lit.h.dunn)
meds <- sites_df %>% group_by(lit) %>% dplyr::summarize(Median = median(
  fac_avgh, na.rm = TRUE), quant = quantile(fac_avgh, probs = 0.75))
meds$letter <- cld3$MonoLetter
fac.h.lit <- ggplot(sites_df, aes(y= fac_avgh, x= lit))+geom_boxplot()+
```

```
  scale_x_discrete(limits = c("None", "Low", "High"))+
  ggtitle("Facultative Seeder Performance")+
  labs(x="Leaf Litter Cover", y="Performance (cm)")+
  theme_bw()+ theme(panel.grid.major = element_blank(),
                    panel.grid.minor=element_blank())+
  geom_text(data=meds, aes(label = letter, x = lit, y = quant),
            vjust = -0.5, hjust = -0.5)
ggarrange(fac.h.lit, fac.h.soil, fac.h.rock, nrow = 1, ncol = 3)
```