FINAL RESEARCH PAPER SUBMITTED TO

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BY

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Title: An Evaluation of 11 Summer Cover Crops for Suitability to Southwest British Columbia

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Abstract

Cover crops have many benefits for farmers including reduced inputs and costs, improved yields, water conservation, and reduced exposure to chemicals. Both winter and summer cover crops can improve soil health, add organic matter, build fertility, and suppress weeds. Cover crops vary in their characteristics and farmers would benefit from having more species-specific information in order to choose the best crop to meet their goals. Most of the available research and information on cover crops in our region is specific to winter cover crops. Eleven species of cover crops were evaluated for their suitability as summer cover crops in Southwest British Columbia. Variables measured were biomass accumulation and canopy coverage. Sorghum sudangrass and mustards performed well on biomass, and mustards performed well on canopy coverage.

Keywords: summer cover crops, aboveground biomass, canopy coverage, green manure

Introduction

Literature Review

The inclusion of cover crops in crop rotations has been presented as a key part of addressing global problems of soil degradation, which involves processes of erosion, declines in soil organic matter, loss of fertility and biodiversity, greater acidification and salinization, and decrease in ecosystem services (Lal 2015). Soil degradation is an important agricultural and ecological issue locally as well. Farms in the Fraser River delta region in Southwest British Columbia have seen declines in soil organic matter over the last 30 years due to the shift from integrated farming to cultivated vegetable production. Without the manure from on-farm livestock, it is more difficult for farmers to maintain soil fertility and soil organic matter (Odhiambo et al. 2012).

The inclusion of cover crops in rotations is one of the four principles of conservation agriculture along with residue retention, integrated nutrient management, and the elimination of tillage, and these principles work together to reduce fuel inputs, increase soil carbon, mitigate soil degradation, and increase soil resilience (Lal 2015). Specific benefits of cover crops include reductions in fertilizer and herbicide use (and costs), improved yields, prevention of erosion, moisture conservation, protection of water quality, and reduced exposure to agrichemicals (Sustainable Agriculture Research and Education [SARE] 2012). In a 2016 survey of 2,102 American farmers by SARE and the Conservation Technology Information Centre (CTIC), those who currently use cover crops reported key benefits as improved soil health, improved yield consistency, and yield advantages (CTIC, 2017).

Cover crops have different growth patterns and nutrient uptake characteristics (Ramirez-Garcia et al. 2015; Wendling et al. 2016) and there is no single cover crop that can provide all the possible benefits that a farmer may need for their particular situation. In order to select the right cover crop, farmers must identify their main goal, the place and time for using the cover crop, and narrow down to the specific traits they need in a cover crop (SARE 2012). Summer cover crops may be used to meet similar goals as winter cover crops (e.g. weed suppression, soil building, nitrogen fixation), but they must grow fast enough to be used between early-planted and late-planted cash crops, often for a window of 3-8 weeks (SARE 2012). Biomass accumulation and biomass nitrogen production are also important characteristics linked to a cover crop's ability to benefit soil structure and scavenge nutrients (Ramirez-Garcia et al. 2015; Wendling et al. 2016) and suppress weeds (Wayman et al. 2014). High biomass production is desirable for providing crop residues and increasing soil organic matter (SARE 2012). Summer cover crops in Southwest BC would need to be drought tolerant to limit the need for irrigation in the dry summers (City of Richmond Policy Planning Department 2002).

Interest in summer cover crops is growing, but there is much less research on them compared to winter cover crops (Creamer and Baldwin 2000). This seems to be true for our local region as well. The Winter Cover Crop Program provides financial support to farmers in Delta, BC to plant winter cover crops, and has been operating for almost 30 years (Bradbeer et al. 2012). In a related study, Odhiambo et al. (2012) conducted trials from 1991 to 1995 comparing 16 different cover crop species in terms of growth, soil surface protection, nitrogen uptake, and other characteristics related to winter cover cropping. SARE has regional cover crop information for broad bioregional areas in the US including Northwest Maritime, which may be applicable to a limited extent to Southwest BC. An example of a relevant study on summer cover crops is an evaluation of 13 cover crop species and 7 crop mixtures for vegetable production systems in North Carolina in the southeastern United States (Creamer and Baldwin 2000).

Two commonly recommended summer cover crops are sorghum sudangrass and buckwheat. Sorghum sudangrass is known for adding high amounts of biomass, as well as producing the allelopathic compound sorgoleone that can suppress weeds (SARE 2012). Buckwheat is known for its rapid germination, growth, flowering, and decomposition, which makes it desirable to plant in short windows over the summer between early and late seeded cash crops (SARE 2012). Mustards are generally suggested for cool season planting, and are most notable for producing glucosinolates that degrade into compounds that can suppress pests (SARE 2012). Legumes are not known for biomass production, but they can fix nitrogen and have a lower C:N ratio relative to grasses, which means nutrients are made available faster (SARE 2012). Grasses have a higher C:N ratio and break down slower, therefore adding more organic matter compared to legumes (SARE 2012). This experiment includes sorghum sudangrass, buckwheat, and a number of brassica, legume, and grass species. The objective was to evaluate 11 different cover crops for their suitability as summer cover crops for Southwest British Columbia by comparing biomass accumulation and canopy coverage. One broader goal was to contribute to the current knowledge about cover crops in our region, which seems mostly focused on winter cover crops.

Methods

Experimental Design

The study was carried out on the KPU farm portion of the Garden City Lands in Richmond, BC. The experimental design was a single factor randomized complete block design with three replicates. The experimental units were 12'x12' plots. The treatment factor was cover crop species with 11 levels (Table 1). The 11 different cover crops are barley (*Hordeum vulgare*), buckwheat (*Fagopyrum esculentum*), oats (*Avena sativa*), sorghum sudangrass

(*Sorghum* × *drummondii*), crimson clover (*Trifolium incarnatum*), sweetclover (*Melilotus officinalis*), alfalfa (*Medicago sativa*), cowpeas (*Vigna unguiculata*), white mustard (*Sinapis alba*), brown mustard (*Brassica juncea*), and yellow mustard (*Guillenia flavescens*). The hypothesis was that biomass accumulation and canopy coverage will differ by species.

Summer cover crop	**Seeding rate (lb/acre)**	**Seed supplier**
Barley *(Hordeum vulgare)*	80–125	Unconfirmed
Buckwheat (*Fagopyrum esculentum*)	50-90	William Dam
Oats (*Avena sativa)*	110-140	Unconfirmed
Sorghum sudangrass (*Sorghum* × *drummondii*)	40-50	William Dam
Crimson clover (*Trifolium incarnatum*)	22-30	Unconfirmed
Sweetclover (*Melilotus officinalis*)	10-20	Tourne-Sol Co-operative Farm
Alfalfa (*Medicago sativa*)	15-20	Unconfirmed
Cowpeas (*Vigna unguiculata*)	70-120	Johnny's Select Seeds
White mustard (*Sinapis alba*)	10-15	West Coast Seeds
Brown mustard (*Brassica juncea*)	10-15	Johnny's Select Seeds
Yellow mustard (*Guillenia flavescens*)	10-15	Johnny's Select Seeds

Table 1. List of summer cover crop species, seeding rate, and seed sources. Seeding rate was taken from SARE (2012), except for alfalfa seeding rate which was taken from Johnny's Select Seeds website.

Preparation and Seeding

The site was amended with compost before seeding to address low levels of organic matter. Previously seeded winter cover crops showed signs of nutrient deficiency, particularly phosphorus. Buckwheat and sorghum sudangrass were ordered from William Dam Seeds, cowpeas, brown mustard, and yellow mustard from Johnny's Select Seeds, white mustard from West Coast Seeds, and sweetclover from Tourne-Sol Cooperative Farm. Barley, oats, crimson clover, and alfalfa were sourced from KPU's existing seed supplies. Seeding rates were taken from SARE (2012). Crimson clover and cowpea were not inoculated with rhizobia. Alfalfa and sweetclover were inoculated with the same inoculant. Seeds were planted on July 5 using a precalibrated chest-mounted spreader, except for alfalfa and sweetclover seeds which were spread by hand due to clumping from moisture. Plots were not raked or cultivated after planting, and were irrigated twice after seeding.

Sampling and Data Collection

Mean temperature and precipitation data were taken from the Richmond Nature Park climate station (Figure 1). Green canopy cover was measured weekly for four weeks using the Canopeo app (Patrignani and Ochsner 2015). Canopeo photos were taken with an iPhone held 5 feet above ground level. Aboveground biomass was measured by hand clipping cover crop in 1' x 1' quadrats (3 quadrats per plot) as described in Sullivan and Andrews (2012). Mustard samples were collected on Aug 15 and 22 as they reached seed set stage earlier than other species. All other samples were collected on Aug 29 and 30. Fresh weights were collected in the field. Dry weights were collected by oven-drying samples at 70°C until constant weight was reached, and then weighed.

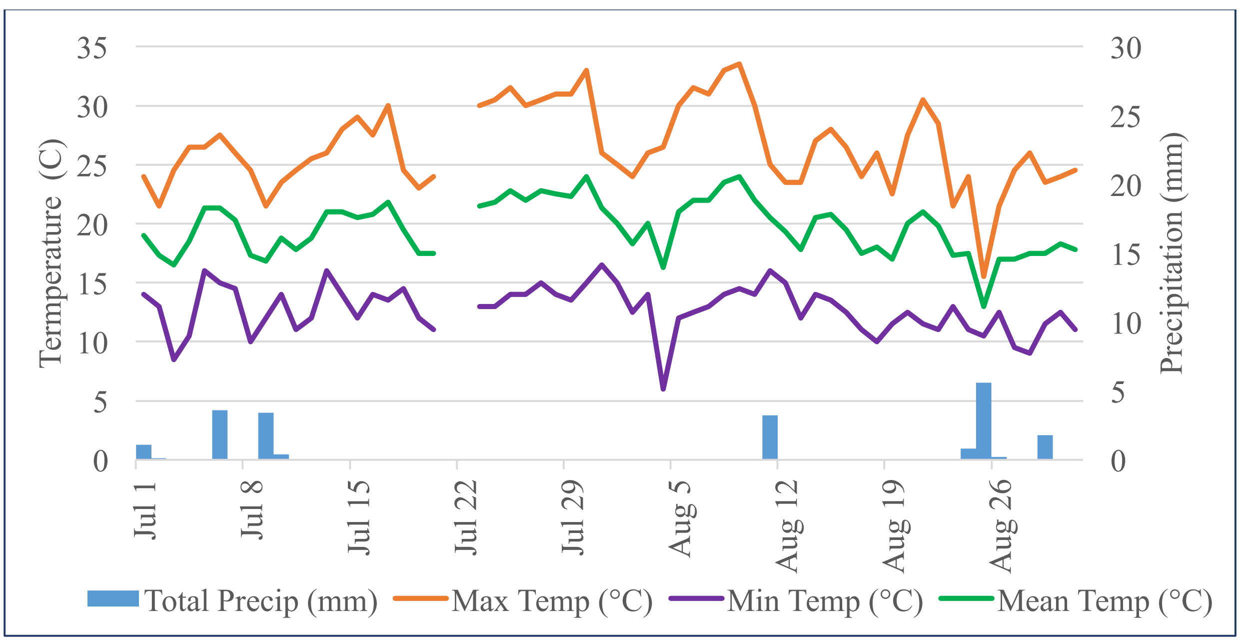

Figure 1. Daily temperature and precipitation readings from Richmond Nature Park climate station from July 1 to August 31, 2018 (Environment Canada n.d.).

Statistical Analysis

All data analysis was conducted in R 3.5.1. Data were tested for normality and transformed using square root (fresh weights and dry weights), arcsine square root (maximum canopy coverage) and logit (canopy coverage over time), and back-transformed for graphs. Maximum canopy coverage and aboveground biomass data were analyzed using a one-way ANOVA, and Tukey's Honestly Significant Difference (HSD) test was used as post-hoc analysis to identify which means were significantly different from each other. The effect of time and species on canopy coverage were analyzed using a repeated measures ANOVA in EZR. Refer to Appendix for R code and output.

Results

Canopy Coverage

Maximum canopy coverage was significantly affected by species ($p = 2.48 \times 10^{-9}$) and block ($p = 8.66 \times 10^{-10}$), but there was no significant interaction effect between species and block ($p = 0.457$). Mustards had the highest maximum canopy coverage, although Tukey's HSD test showed that there were significant differences between means at the high end and low end of the data, but not for means in the middle range (Figure 2). Mustards reached maximum coverage at 27 days and then declined slightly, while all other crops were still increasing by the last date of measurement (48 days). Repeated measures ANOVA showed that species, time, blocking, and their interactions had significant effects on overall canopy coverage, except for the interaction between species and block (Table 2). However, the p-value for Mauchly's Test of Sphericity was 0.00044448 for all tests, indicating a violation of sphericity (Laerd Statistics n.d.).

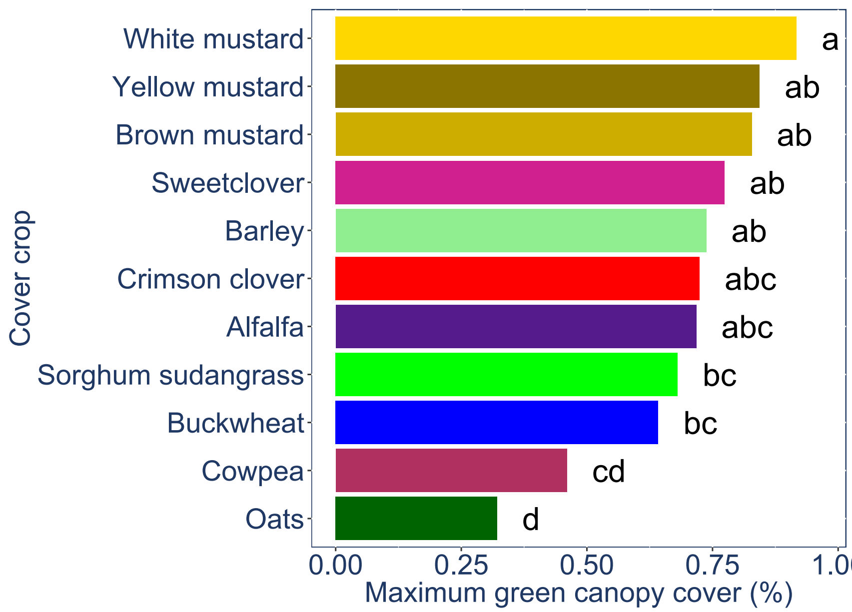

Figure 2. Maximum fractional green canopy coverage of each cover crop species. Means labeled with the same letters are not significantly different (Tukey's HSD, α=0.05).

Effect	SSn	d.f.	Error SS	d.f.	F value	P value
Species	622.29	10	151.550	66	27.1006	$<2.2e^{-16}$
Time	703.59	3	31.518	198	1473.3319	$<2.2e^{-16}$
Block	247.01	2	151.550	66	53.7859	$1.387e^{-14}$
Species x Time	41.55	30	31.518	198	8.7012	$<2.2e^{-16}$
Species x Block	54.20	20	151.550	66	1.1801	0.2991
Time x Block	9.46	6	31.518	198	9.9075	$1.483e^{-9}$
Species x Time x Block	21.10	60	31.518	198	2.2091	$2.308e^{-5}$

Table 2. Results for Type III repeated measures ANOVA regarding the effects of cover crop species, time, block, and interactions on canopy coverage. Mauchly's Test for Sphericity p value for all tests is 0.00044448.

Biomass Accumulation

Sorghum sudangrass and white mustard generally had the highest biomass and legumes the lowest (Figures 3 and 4). Fresh weight was significantly affected by species ($p = 2.7 \times 10^{-10}$) and block ($p = 0.0342$), but there was no significant interaction between the two ($p = 0.3901$). Sorghum sudangrass had the highest fresh weight and was significantly different from all except white mustard (Figure 3). Similar to fresh weight, dry weight was significantly affected by species (p = 0.00000107) and block (p = 0.00513) and again had no interaction effect.

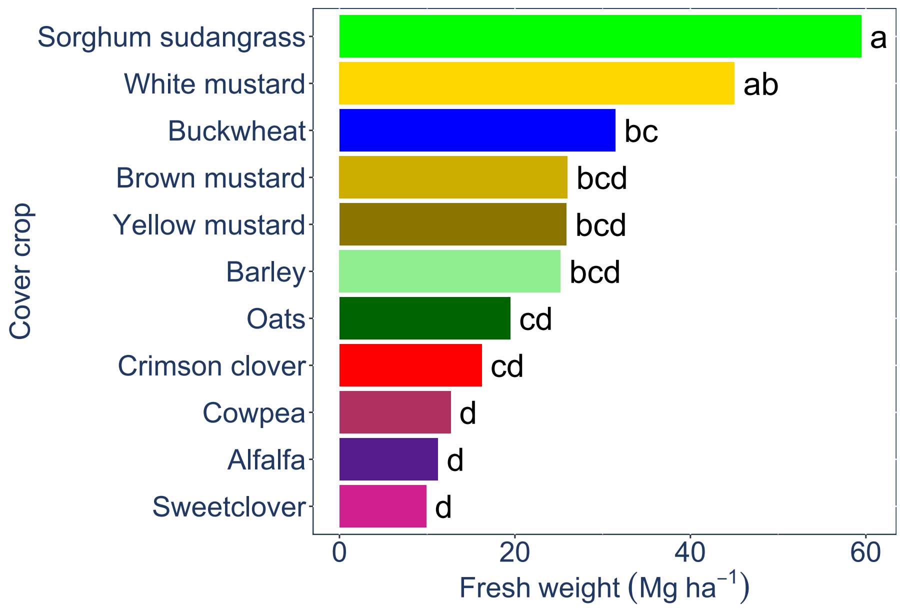

Figure 3. Aboveground fresh biomass of each cover crop species. Means labeled with the same letters are not significantly different (Tukey's HSD, α=0.05).

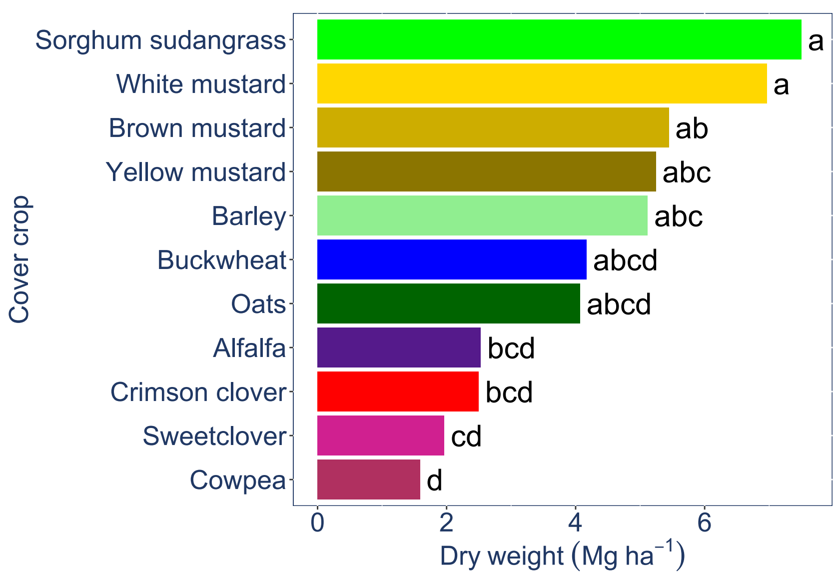

Figure 4. Aboveground dry biomass of each cover crop species. Means labeled with the same letters are not significantly different (Tukey's HSD, α=0.05).

Discussion

Results were consistent with the expectation that species will differ in biomass production and canopy coverage. Sorghum sudangrass performed as expected in terms of producing high biomass. It is possible that sorghum sudangrass would have produced even more biomass with additional irrigation. An irrigated stand of the same crop was planted in another area of the field and was visibly much taller than the experimental stand that received less irrigation.

It was also unsurprising that legumes produced the lowest biomass. As previously mentioned, legumes are typically grown not for their biomass production but for their ability to fix nitrogen. Nitrogen production was included in the original experimental plan but was excluded due to lack of time. This would be valuable to explore in a future iteration of this study. Grass-legume cover crop mixes are also commonly used (SARE 2012) and would be an interesting topic to research in the future. However, one barrier is the difficulty in procuring proper inoculant for organic legume seeds. In sourcing supplies for this experiment, there were suppliers who would ship the right inoculant to the US but not to Canada. Alfalfa and sweetclover were inoculated, but crimson clover and cowpea were not.

The mustards' good performance on both biomass and canopy coverage was surprising given that they tend to be characterized as cool season cover crops (SARE 2012), but this could be because of our region's moderate summer temperatures. The mean daily temperature from July 1 to August 31, 2018 averaged out to 19.6°C, although the maximum daily temperatures over the same period averaged out to 26.9°C (Environment Canada n.d.). Plots were not raked or cultivated after seeding, which means seeds were left on the soil surface rather than buried. This likely affected the germination of the plots. It is possible that the small size of the mustard seeds allowed them to have greater soil contact, which would have improved their germination rate and given them a head start over the other species.

Another advantage of mustards, shared by buckwheat, is rapid flowering. Some plots were flowering 27 days after planting, and all mustard and buckwheat plots were flowering 34 days after planting. A number of pollinators were observed in the plots, which was a benefit considering that the KPU research farm was newly established that summer. However, mustard weeds were observed at the experimental site 2 to 3 months after the termination of the plots. It seems that the mustards were very quickly able to set seed and were not terminated fast enough.

Weed suppression is another characteristic that would be beneficial to examine in summer cover crops. Weed biomass was part of the original experimental plan but was excluded due to the incompatibility of measuring canopy coverage and weed biomass at the same time. The Canopeo app used for canopy coverage does not distinguish between crop canopy and weed canopy, so weeds were removed from the plot sections that were photographed for canopy coverage measurements.

For the repeated measures ANOVA for canopy coverage, the assumption of sphericity was violated. Sphericity is similar to homogeneity of variances in a one-way ANOVA (Laerd Statistic n.d.). The violation of sphericity can be addressed using three corrections: the lower bound estimate, Greenhouse-Geisser correction, and Huynh-Feldt correction (Laerd Statistics n.d.), but are outside my statistical understanding and knowledge of R.

Conclusion

Sorghum sudangrass and mustards performed the best in terms of producing high amounts of biomass over an 8-week period in the summer, and mustards performed the best in terms of canopy coverage. These crops are known to have pest management benefits through allelopathy (sorghum sudangrass), production of biofumigants (mustards), and flowering to attract pollinators and beneficial insects (mustards). However, mustards are quick to set seed and are cool season crops so they pose a greater risk of creating a weed problem if not terminated properly and on time.

Acknowledgements

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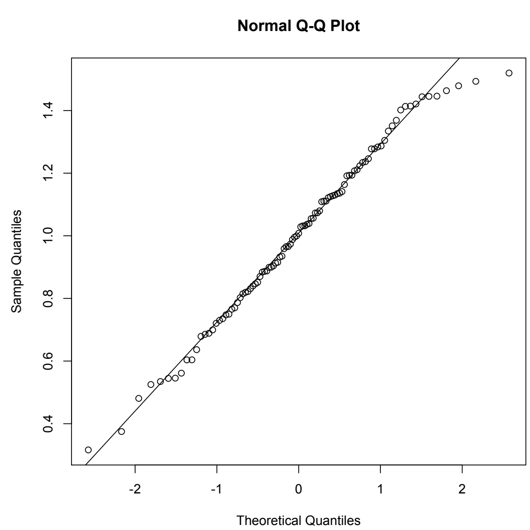
Appendix

Maximum Canopy Cover

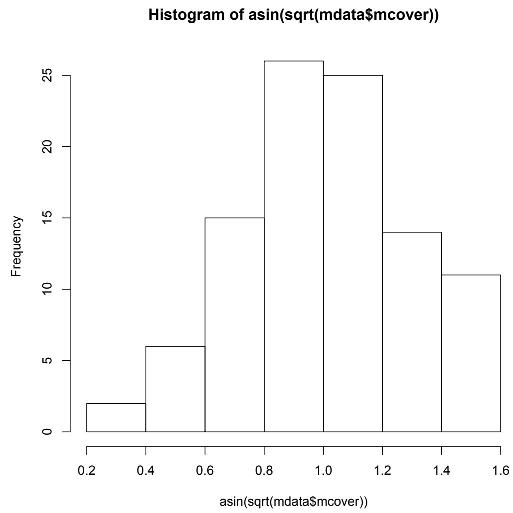
```
> mdata<-read.delim(pipe("pbpaste"))
> mdata
   mblock             mcrop mcover
1       A           Alfalfa 0.5842
2       A           Alfalfa 0.6174
3       A           Alfalfa 0.5367
4       B           Alfalfa 0.8842
5       B           Alfalfa 0.8983
6       B           Alfalfa 0.9165
7       C           Alfalfa 0.7724
8       C           Alfalfa 0.5611
9       C           Alfalfa 0.5458
10      A            Barley 0.4846
11      A            Barley 0.5170
12      A            Barley 0.9198
13      B            Barley 0.8630
14      B            Barley 0.8115
15      B            Barley 0.9843
16      C            Barley 0.7364
17      C            Barley 0.5981
18      C            Barley 0.4803
19      A         Buckwheat 0.2684
20      A         Buckwheat 0.6836
21      A         Buckwheat 0.6004
22      B         Buckwheat 0.8227
23      B         Buckwheat 0.7366
24      B         Buckwheat 0.8265
25      C         Buckwheat 0.8142
26      C         Buckwheat 0.4006
27      C         Buckwheat 0.5542
28      A            Cowpea 0.0967
29      A            Cowpea 0.3532
30      A            Cowpea 0.3225
31      B            Cowpea 0.7077
32      B            Cowpea 0.8432
33      B            Cowpea 0.6134
34      C            Cowpea 0.7041
35      C            Cowpea 0.2596
36      C            Cowpea 0.2834
37      A    Crimson clover 0.6130
38      A    Crimson clover 0.5658
39      A    Crimson clover 0.6263
40      B    Crimson clover 0.9974
41      B    Crimson clover 0.9717
```

42	B	Crimson clover	0.8908
43	C	Crimson clover	0.6449
44	C	Crimson clover	0.4354
45	C	Crimson clover	0.4040
46	A	Oats	0.2139
47	A	Oats	0.2513
48	A	Oats	0.4447
49	B	Oats	0.3942
50	B	Oats	0.4145
51	B	Oats	0.7430
52	C	Oats	0.5014
53	C	Oats	0.2692
54	C	Oats	0.1341
55	A	Sorghum sudangrass	0.3223
56	A	Sorghum sudangrass	0.8014
57	A	Sorghum sudangrass	0.7407
58	B	Sorghum sudangrass	0.7776
59	B	Sorghum sudangrass	0.7566
60	B	Sorghum sudangrass	0.8737
61	C	Sorghum sudangrass	0.6473
62	C	Sorghum sudangrass	0.6016
63	C	Sorghum sudangrass	0.5294
64	A	Sweetclover	0.7720
65	A	Sweetclover	0.7153
66	A	Sweetclover	0.9309
67	B	Sweetclover	0.5340
68	B	Sweetclover	0.8163
69	B	Sweetclover	0.8641
70	C	Sweetclover	0.7578
71	C	Sweetclover	0.6764
72	C	Sweetclover	0.8181
73	B	Brown mustard	0.9940
74	B	Brown mustard	0.9845
75	C	Brown mustard	0.9598
76	B	Brown mustard	0.8761
77	A	Brown mustard	0.8643
78	C	Brown mustard	0.6762
79	A	Brown mustard	0.6701
80	C	Brown mustard	0.6285
81	A	Brown mustard	0.4502
82	A	White mustard	0.9216
83	A	White mustard	0.8029
84	A	White mustard	0.9840
85	B	White mustard	0.9166
86	B	White mustard	0.9777
87	B	White mustard	0.9754
88	C	White mustard	0.9452
89	C	White mustard	0.8926

```
90       C       White mustard 0.6971
91       A      Yellow mustard 0.7339
92       A      Yellow mustard 0.4621
93       A      Yellow mustard 0.8215
94       B      Yellow mustard 0.9525
95       B      Yellow mustard 0.9885
96       B      Yellow mustard 0.9757
97       C      Yellow mustard 0.9916
98       C      Yellow mustard 0.4644
99       C      Yellow mustard 0.8030

> shapiro.test(mdata$mcover)

	Shapiro-Wilk normality test

data:  mdata$mcover
W = 0.95085, p-value = 0.001012

> shapiro.test(asin(sqrt(mdata$mcover)))

	Shapiro-Wilk normality test

data:  asin(sqrt(mdata$mcover))
W = 0.98589, p-value = 0.3743

> qqnorm(asin(sqrt(mdata$mcover)))
> qqline(asin(sqrt(mdata$mcover)))
```




```
> hist(asin(sqrt(mdata$mcover)))
```



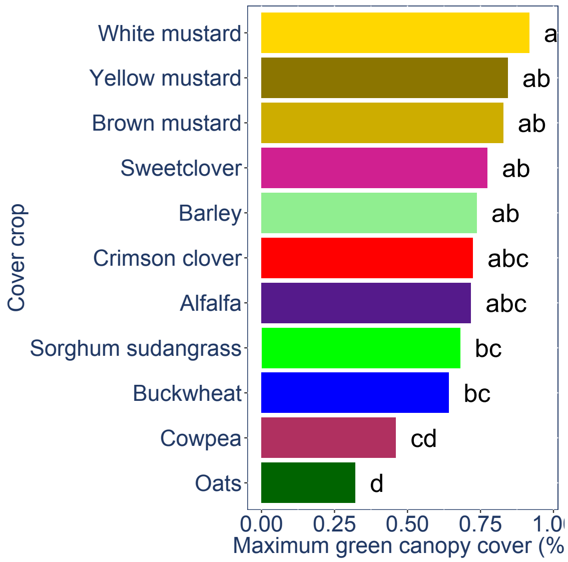

```
> aov.mdata<-aov(asin(sqrt(mdata$mcover))~mdata$mcrop*mdata$mblock)
> summary(aov.mdata)
                         Df Sum Sq Mean Sq F value   Pr(>F)    
mdata$mcrop              10 2.9241  0.2924   9.215 2.48e-09 ***
mdata$mblock              2 1.8473  0.9236  29.107 8.66e-10 ***
mdata$mcrop:mdata$mblock 20 0.6447  0.0322   1.016    0.457    
Residuals                66 2.0943  0.0317                     
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> library(agricolae)
> HSD.test(aov.mdata,"mdata$mcrop",console=TRUE)

Study: aov.mdata ~ "mdata$mcrop"

HSD Test for asin(sqrt(mdata$mcover))

Mean Square Error:  0.03173256

mdata$mcrop,  means

                   asin.sqrt.mdata.mcover..       std r       Min      Max
Alfalfa                           1.0105407 0.1942474 9 0.8221312 1.277652
Barley                            1.0328915 0.2453851 9 0.7656931 1.445166
Brown mustard                     1.1431214 0.2636196 9 0.7355155 1.493259
Buckwheat                         0.9293176 0.2109145 9 0.5445969 1.141168
Cowpea                            0.7456922 0.2784783 9 0.3162095 1.163662
Crimson clover                    1.0179154 0.2963736 9 0.6887983 1.519784
Oats                              0.6511694 0.1970509 9 0.3749185 1.039152
Sorghum sudangrass                0.9698461 0.1822033 9 0.6037272 1.207468
Sweetclover                       1.0753784 0.1390795 9 0.8194244 1.304802
White mustard                     1.2792449 0.1513625 9 0.9879968 1.443965
Yellow mustard                    1.1643632 0.2858187 9 0.7474618 1.479016
```

```
Alpha: 0.05 ; DF Error: 66
Critical Value of Studentized Range: 4.715093

Minimun Significant Difference: 0.2799765

Treatments with the same letter are not significantly different.

                   asin(sqrt(mdata$mcover)) groups
White mustard                     1.2792449      a
Yellow mustard                    1.1643632     ab
Brown mustard                     1.1431214     ab
Sweetclover                       1.0753784     ab
Barley                            1.0328915     ab
Crimson clover                    1.0179154    abc
Alfalfa                           1.0105407    abc
Sorghum sudangrass                0.9698461     bc
Buckwheat                         0.9293176    bcd
Cowpea                            0.7456922     cd
Oats                              0.6511694      d
```

Results of Tukey's HSD were backtransformed in Excel, sorted by group, and imported back into R as the mtablesort data set. Backtransformation was done by squaring the sine of each asin(sqrt(mdata$mcover)) value.

```
> mtablesort
                Mcrop asinsqrtx     backx Mgroup
10      White mustard 1.2792450 0.9173791      a
11     Yellow mustard 1.1643630 0.8437097     ab
3       Brown mustard 1.1431210 0.8279769     ab
9         Sweetclover 1.0753780 0.7739951     ab
2              Barley 1.0328920 0.7375104     ab
6      Crimson clover 1.0179150 0.7242264    abc
1             Alfalfa 1.0105410 0.7176114    abc
8  Sorghum sudangrass 0.9698461 0.6802929     bc
4           Buckwheat 0.9293176 0.6419403     bc
5              Cowpea 0.7456922 0.4603358     cd
7                Oats 0.6026716 0.3213137      d

> library(ggplot2)
> m.plot<-
ggplot(mtablesort,aes(x=factor(Mcrop),y=backx,fill=mtablesort$Mcrop))+geom_ba
r(stat="identity",position=position_dodge(1))+labs(x="Cover crop",y="Maximum
green canopy cover
(%)")+coord_flip()+scale_x_discrete(limits=rev(levels(mtablesort$Mcrop)))+geo
m_text(size=8,hjust="left",aes(x=Mcrop,y=backx+.05,label=Mgroup))+theme(legen
d.position="none",panel.background=element_rect(fill="white",colour="#203864"
),axis.title.x=element_text(size=20,colour="#203864"),axis.text.x=element_tex
```

```
t(size=20,colour="#203864"),axis.title.y=element_text(size=20,colour="#203864
"),axis.text.y=element_text(size=20,colour="#203864"))+scale_fill_manual(valu
es=c("gold","gold4","gold3","violetred","lightgreen","red","purple4","green1"
,"blue1","maroon","darkgreen"))
> m.plot
```

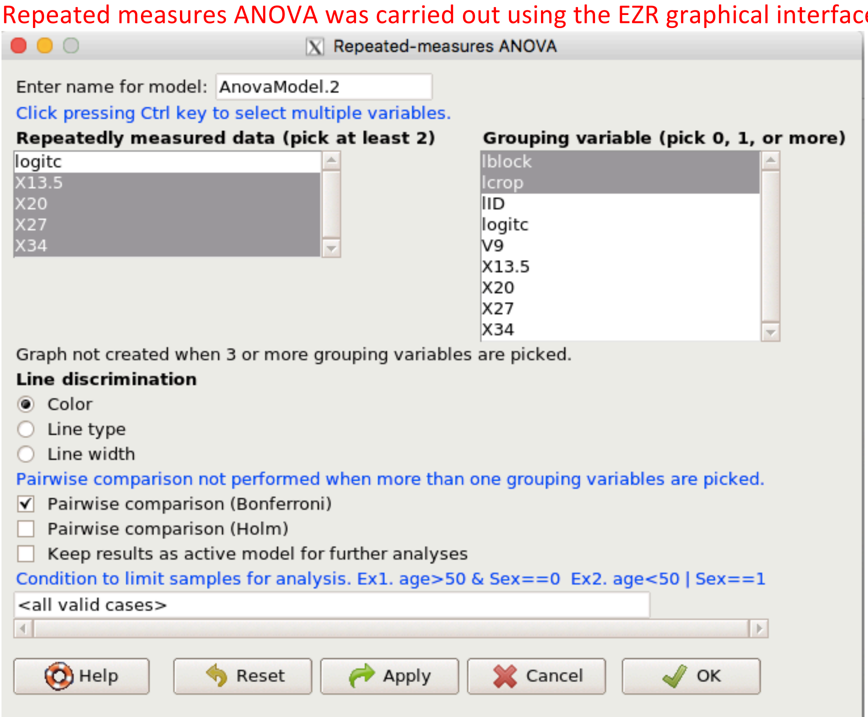


Repeated measures ANOVA for Canopy Coverage

In Excel, canopy cover data was transformed using a logit transformation, and then laid out in a wide table format. The first 15 rows are shown below. This table was imported into R and named as the wide dataset. The column names w13.5, w20, w27, and w34 refer to the number of days from planting that canopy cover data was measured.

ldays	lID	lcrop	lblock	w13.5	w20	w27	w34
13.5	A1	White mustard	A	-2.117578	-0.1342011	2.289456	2.464287
13.5	A1	White mustard	A	-2.317303	-1.832002	-0.06682486	1.404519
13.5	A1	White mustard	A	-1.151583	1.597009	3.459054	4.119037
13.5	A10	Crimson clover	A	-2.773014	-1.787333	-0.793116	-0.3747241
13.5	A10	Crimson clover	A	-3.334693	-2.305118	-1.459786	-1.306936
13.5	A10	Crimson clover	A	-2.895026	-1.887761	-0.8511103	-0.6207979
13.5	A11	Alfalfa	A	-2.893014	-2.362212	-0.6265202	-0.6089445
13.5	A11	Alfalfa	A	-2.820998	-1.70664	-0.47345	-0.6561722
13.5	A11	Alfalfa	A	-2.740946	-1.869496	-0.3540527	-0.6610668
13.5	A2	Oats	A	-4.112705	-3.68847	-2.507989	-1.640478
13.5	A2	Oats	A	-3.960355	-2.86718	-2.042622	-1.457826
13.5	A2	Oats	A	-3.03888	-2.303906	-1.224759	-0.9946226
13.5	A3	Sweetclover	A	-4.212026	-3.532555	-1.282647	-1.024766
13.5	A3	Sweetclover	A	-4.795387	-4.345427	-2.355874	-1.604885
13.5	A3	Sweetclover	A	-5.680574	-2.513748	-0.6690928	0.2965544

Repeated measures ANOVA was carried out using the EZR graphical interface:



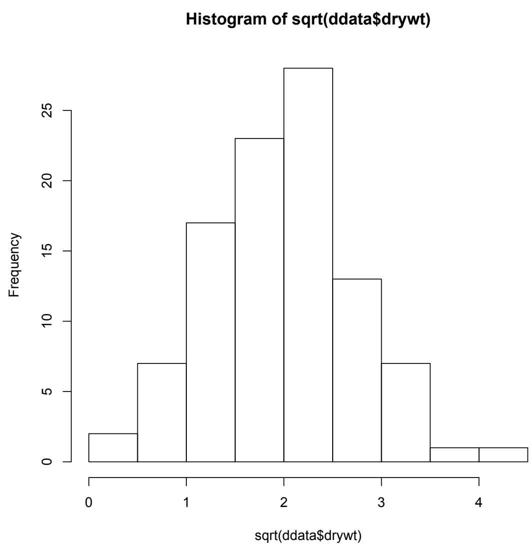
Output:

```
> #####Repeated-measures ANOVA#####
> TempDF <-  wide
> TempDF$Factor1.lblock <- factor(TempDF$lblock)
> contrasts(TempDF$Factor1.lblock) <- "contr.Sum"
> TempDF$Factor2.lcrop <- factor(TempDF$lcrop)
> contrasts(TempDF$Factor2.lcrop) <- "contr.Sum"
> #Convert to long format to draw graph
> n <- length(TempDF[,1])
> TempDF$TempID <- c(1:n)
> TempDF2 <- data.frame(TempID=TempDF$TempID, X13.5=TempDF$X13.5,
X20=TempDF$X20,
+   X27=TempDF$X27, X34=TempDF$X34, lblock=TempDF$lblock, lcrop=TempDF$lcrop)
> TempDF2 <- na.omit(TempDF2)
> TempDF3 <- reshape(TempDF2, idvar="TempID", varying=list(c("X13.5", "X20",
"X27",
+   "X34")), v.names="data", direction="long")
> RepeatNumber <- c("X13.5", "X20", "X27", "X34")

> nvar <- length(TempDF3$time)
> for (i in 1:nvar){TempDF3$time2[i] <- RepeatNumber[TempDF3$time[i]]}
> for (i in 1:length(levels(factor(TempDF3$lblock)))){windows(); par(lwd=1,
las=1,
+   family="sans", cex=1, mgp=c(3.0,1,0));
+
StatMedplotMeans(TempDF3$data[TempDF3$lblock==levels(factor(TempDF3$lblock))[
i]],
+   factor(TempDF3$time2[TempDF3$lblock==levels(factor(TempDF3$lblock))[i]]),
+   factor(TempDF3$lcrop[TempDF3$lblock==levels(factor(TempDF3$lblock))[i]]),
+   error.bars="sd", xlab="", ylab="", legend.lab="lcrop",
main=paste("lblock", " : ",
+   levels(factor(TempDF3$lblock))[i]), , lty=1, lwd=1)}

> AnovaModel.1 <- lm(cbind(X13.5, X20, X27, X34) ~
Factor1.lblock*Factor2.lcrop,
+   data=TempDF, na.action=na.omit)
> time <- factor(c("X13.5", "X20", "X27", "X34"))
> time <- data.frame(Time = time)
> res <- NULL
> res <- Anova(AnovaModel.1, idata=time, idesign=~Time, type="III")
> summary(res, multivariate=FALSE)

Univariate Type III Repeated-Measures ANOVA Assuming Sphericity

                             Sum Sq num Df Error SS den Df  F value    Pr(>F)
(Intercept)                  760.31      1  151.550     66 331.1165 < 2.2e-16 ***
Factor1.lblock               247.01      2  151.550     66  53.7859 1.387e-14 ***
Factor2.lcrop                622.29     10  151.550     66  27.1006 < 2.2e-16 ***
```

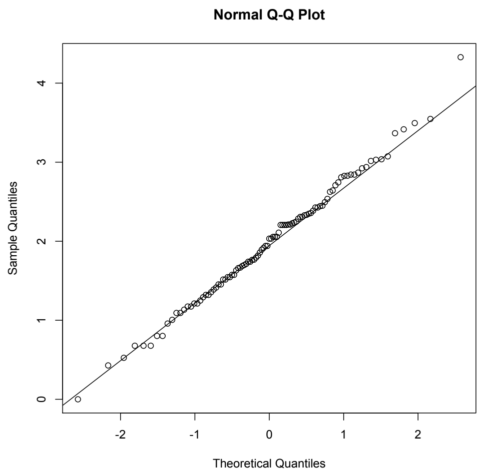
```
Factor1.lblock:Factor2.lcrop       54.20     20  151.550     66    1.1801    0.2991    
Time                              703.59      3   31.518    198 1473.3319 < 2.2e-16 ***
Factor1.lblock:Time                 9.46      6   31.518    198    9.9075 1.483e-09 ***
Factor2.lcrop:Time                 41.55     30   31.518    198    8.7012 < 2.2e-16 ***
Factor1.lblock:Factor2.lcrop:Time  21.10     60   31.518    198    2.2091 2.308e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Mauchly Tests for Sphericity

                                  Test statistic    p-value
Time                                     0.70769 0.00044448
Factor1.lblock:Time                      0.70769 0.00044448
Factor2.lcrop:Time                       0.70769 0.00044448
Factor1.lblock:Factor2.lcrop:Time        0.70769 0.00044448


Greenhouse-Geisser and Huynh-Feldt Corrections
 for Departure from Sphericity

                                   GG eps    Pr(>F[GG])    
Time                              0.84546     < 2.2e-16 ***
Factor1.lblock:Time               0.84546 0.00000002156 ***
Factor2.lcrop:Time                0.84546     < 2.2e-16 ***
Factor1.lblock:Factor2.lcrop:Time 0.84546 0.00008810031 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

                                    HF eps    Pr(>F[HF])
Time                              0.882067 1.694729e-119
Factor1.lblock:Time               0.882067  1.142673e-08
Factor2.lcrop:Time                0.882067  2.246768e-20
Factor1.lblock:Factor2.lcrop:Time 0.882067  6.408347e-05
```

Dry Weight

```
> shapiro.test(ddata$drywt)

      Shapiro-Wilk normality test

data:  ddata$drywt
W = 0.91139, p-value = 0.000005571

> shapiro.test(sqrt(ddata$drywt))

      Shapiro-Wilk normality test

data:  sqrt(ddata$drywt)
W = 0.99522, p-value = 0.9812

> hist(sqrt(ddata$drywt))
```




```
> qqnorm(sqrt(ddata$drywt))
> qqline(sqrt(ddata$drywt))
```



Two outliers were identified and removed, one from buckwheat (value=0) and one from white mustard (value=1.6666667).

```
> aov.ddata<-aov(sqrt(ddata$drywt)~ddata$dcrop*ddata$dblock)
> summary(aov.ddata)
                          Df Sum Sq Mean Sq F value     Pr(>F)    
ddata$dcrop               10 21.806   2.181   6.358 0.00000107 ***
ddata$dblock               2  3.931   1.966   5.731    0.00513 ** 
ddata$dcrop:ddata$dblock  20  6.260   0.313   0.913    0.57345    
Residuals                 64 21.952   0.343                       
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> HSD.test(aov.ddata,"ddata$dcrop",console=TRUE)

Study: aov.ddata ~ "ddata$dcrop"

HSD Test for sqrt(ddata$drywt) 

Mean Square Error:  0.3429958 

ddata$dcrop,  means

                    sqrt.ddata.drywt.       std r       Min      Max
Alfalfa                      1.590522 0.4916457 9 0.8017429 2.206094
Barley                       2.262358 0.5805107 9 1.5151515 2.937988
Brown mustard                2.333548 0.4847525 9 1.6666667 3.073181
Buckwheat                    2.042012 0.4684149 8 1.2121213 2.443108
Cowpeas                      1.260506 0.5168676 9 0.4285495 1.916532
Crimson clover               1.580275 0.4575998 9 1.0050378 2.247333
Oats                         2.017555 0.7270152 9 0.6775963 2.842676
Sorghum sudangrass           2.738728 1.1331435 9 0.5248639 4.328138
Sweetclover                  1.401571 0.4604303 9 0.6775963 2.032789
White mustard                2.638953 0.3691807 8 2.2110832 3.366501
Yellow mustard               2.290033 0.6260072 9 1.4142136 3.415651
```

```
Alpha: 0.05 ; DF Error: 64
Critical Value of Studentized Range: 4.720267

Groups according to probability of means differences and alpha level( 0.05 )

Treatments with the same letter are not significantly different.

                   sqrt(ddata$drywt) groups
Sorghum sudangrass          2.738728      a
White mustard               2.638953      a
Brown mustard               2.333548     ab
Yellow mustard              2.290033    abc
Barley                      2.262358    abc
Buckwheat                   2.042012   abcd
Oats                        2.017555   abcd
Alfalfa                     1.590522    bcd
Crimson clover              1.580275    bcd
Sweetclover                 1.401571     cd
Cowpeas                     1.260506      d
```

Results of Tukey's HSD were backtransformed in Excel, sorted by group, and imported back into R as the dtable data set. Backtransformation was done by squaring each ddata$drywt value into the dback column.

```
> dtable<-read.delim(pipe("pbpaste"))
> dtable
                dcrop dgroups    dback
1  sorghum sudangrass       a 7.500631
2       white mustard       a 6.964073
3       brown mustard      ab 5.445446
4      yellow mustard     abc 5.244251
5              barley     abc 5.118264
6           buckwheat    abcd 4.169813
7                oats    abcd 4.070528
8             alfalfa     bcd 2.529760
9      crimson clover     bcd 2.497269
10        sweetclover      cd 1.964401
11            cowpeas       d 1.588875
```

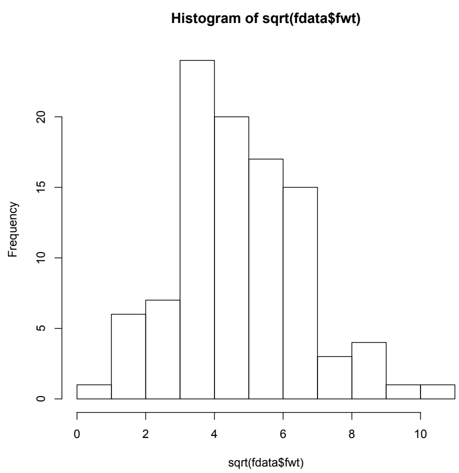
Graphing was done on a workstation in the Sustainable Agriculture offices so I cannot retrieve the R code. It was something similar to the code below, except that I had re-ordered the levels of the dcrop factor so that highest values would be on top (i.e. sorghum sudangrass) and lowest would be on the bottom (i.e. cowpeas).

```
> d.plotd<-
ggplot(dtable,aes(x=factor(dcrop),y=dback,fill=dcrop))+geom_bar(stat="identit
y",,position=position_dodge(1))+labs(x="Cover
crop",y=expression(Dry~weight~(Mg~ha^{-
1}))+coord_flip()+scale_x_discrete(limits=rev(levels(dtable$dcrop)))+geom_te
```

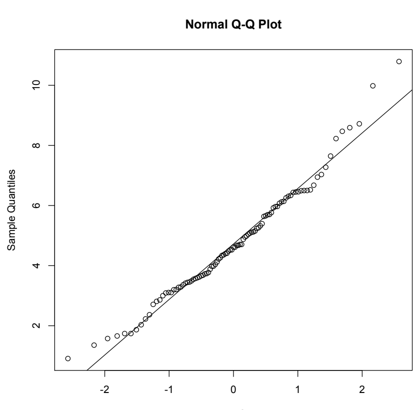
```
xt(size=8,hjust="left",aes(x=dcrop,y=dback+.1,label=dgroups))+theme(legend.po
sition="none",panel.background=element_rect(fill="white",colour="#203864"),ax
is.title.x=element_text(size=20,colour="#203864"),axis.text.x=element_text(si
ze=20,colour="#203864"),axis.title.y=element_text(size=20,colour="#203864"),a
xis.text.y=element_text(size=20,colour="#203864"))+scale_fill_manual(values=c
("green1","gold","gold3","gold4","lightgreen","blue1","darkgreen","purple4","
red","violetred","maroon"))
```

Fresh Weight

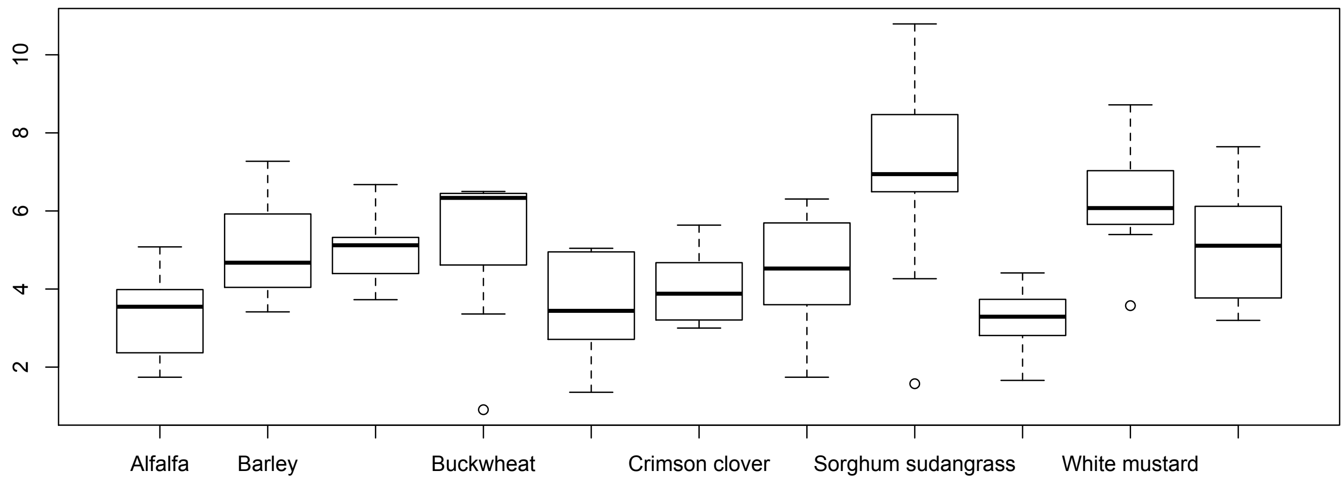
```
> fdata<-read.delim(pipe("pbpaste"))
> shapiro.test(fdata$fwt)

	Shapiro-Wilk normality test

data:  fdata$fwt
W = 0.85029, p-value = 0.00000001376

> shapiro.test(sqrt(fdata$fwt))

	Shapiro-Wilk normality test

data:  sqrt(fdata$fwt)
W = 0.97638, p-value = 0.07182

> hist(sqrt(fdata$fwt))
```




```
> summary(sqrt(fdata$fwt))
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.9091  3.4749  4.6156  4.7424  5.9659 10.7906 
> qqnorm(sqrt(fdata$fwt))
> qqline(sqrt(fdata$fwt))
```

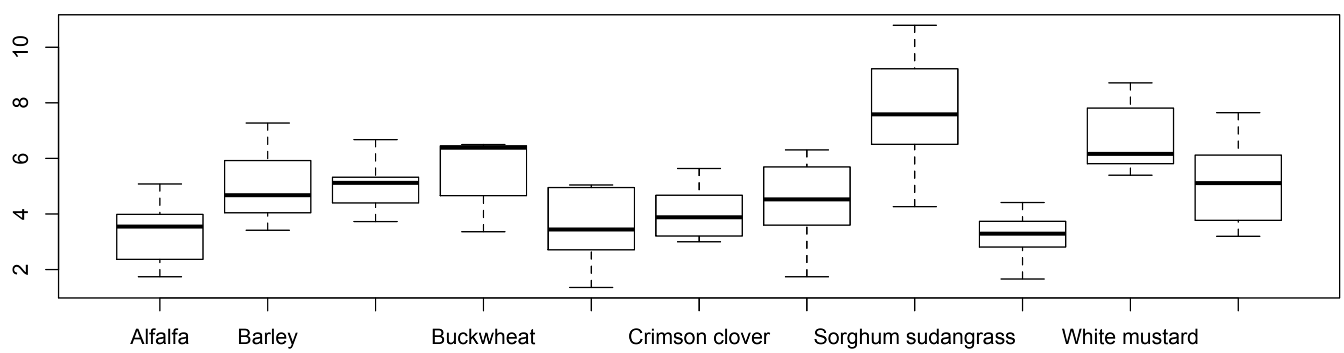


```
> plot(fdata$fcrop,sqrt(fdata$fwt))
```



Outliers were identified using the boxplot and removed from buckwheat, sorghum sudangrass, and white mustard using fix().

```
> fix(fdata)
> plot(fdata$fcrop,sqrt(fdata$fwt))
```




```
> aov.fdata<-aov(sqrt(fdata$fwt)~fdata$fcrop*fdata$fblock)
> summary(aov.fdata)
                         Df Sum Sq Mean Sq F value  Pr(>F)    
fdata$fcrop              10 168.41  16.841  10.649 2.7e-10 ***
fdata$fblock              2  11.27   5.635   3.563  0.0342 *  
fdata$fcrop:fdata$fblock 20  34.21   1.710   1.082  0.3901    
Residuals                63  99.63   1.581                    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> HSD.test(aov.fdata,"fdata$fcrop",console=TRUE)

Study: aov.fdata ~ "fdata$fcrop"

HSD Test for sqrt(fdata$fwt)

Mean Square Error:  1.581434

fdata$fcrop,  means

                  sqrt.fdata.fwt.       std r      Min       Max
Alfalfa                  3.349459 1.1001191 9 1.740777  5.079714
Barley                   5.019235 1.2983592 9 3.414979  7.272727
Brown mustard            5.097849 0.9857799 9 3.726780  6.674995
Buckwheat                5.607055 1.2122770 8 3.360769  6.499276
Cowpea                   3.558014 1.3519974 9 1.355193  5.043429
Crimson clover           4.025833 0.9493561 9 2.999847  5.636690
Oats                     4.412555 1.4361319 9 1.740777  6.305652
Sorghum sudangrass       7.710920 2.0994360 8 4.264015 10.790602
Sweetclover              3.141380 0.9328397 9 1.659765  4.412188
White mustard            6.710194 1.2914676 8 5.395471  8.717798
Yellow mustard           5.086282 1.4167081 9 3.197221  7.644896

Alpha: 0.05 ; DF Error: 63
Critical Value of Studentized Range: 4.722979

Groups according to probability of means differences and alpha level( 0.05 )

Treatments with the same letter are not significantly different.

                  sqrt(fdata$fwt) groups
Sorghum sudangrass       7.710920      a
White mustard            6.710194     ab
Buckwheat                5.607055     bc
Brown mustard            5.097849    bcd
Yellow mustard           5.086282    bcd
Barley                   5.019235    bcd
Oats                     4.412555     cd
Crimson clover           4.025833     cd
Cowpea                   3.558014      d
Alfalfa                  3.349459      d
Sweetclover              3.141380      d
```

Similar to dry weight, results of Tukey's HSD were backtransformed in Excel, sorted by group, and imported back into R as the ftable data set. Backtransformation was done by squaring each fdata$fwt value into the backF column.

```
> ftable<-read.delim(pipe("pbpaste"))
```

```
> ftable
                fcrop   Fmeans     backF Fgroup
1  Sorghum sudangrass 7.710920 59.458287      a
2       White mustard 6.710194 45.026704     ab
3           Buckwheat 5.607055 31.439066     bc
4       Brown mustard 5.097849 25.988064    bcd
5      Yellow mustard 5.086282 25.870265    bcd
6              Barley 5.019235 25.192720    bcd
7                Oats 4.412555 19.470642     cd
8      Crimson clover 4.025833 16.207331     cd
9              Cowpea 3.558014 12.659464      d
10            Alfalfa 3.349459 11.218876      d
11        Sweetclover 3.141380  9.868268      d
```

Graphing was done in the same way as dry weight as well (code not shown).