Image analysis of Festuca seeds

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Methods

Image analysis was used to explore a potential relationship between seed size and ploidy level in Festuca species. Seeds from each accessions were randomly selected and imaged with an Epson Perfection V6 flatbed scanner at 600 dpi (dots per inch) with size 1987 (width) by 2169 (length) pixels. The TIF images (Tagged Image File Format) were processed with a custom Python script (https://github.com/joanmanbar/Seed_Morphology) that transformed the original images to threshold and measure the seed length and width respectively as the length (in pixels) of the major and minor axes of a fitted ellipse, whereas the area is calculated as the number of pixels in the seed. The script returned a dataset containing the image name, the seed number and their dimensional attributes. The data analysis was performed in R (R Core Team, 2014) by fitting liner models with seed area, length, and width as response and the ploidy level as predictor. To remove potential artifacts, we filtered out the seeds that were not within the 45th and 55th quantile. Finally, we used the qaplot2 package (Wickham, 2009) for plots and figures.

Preparing the data

```
# Get working directory
mydir <- getwd()</pre>
# Read data
mydata1 <- read.csv(paste0(mydir, '/Seeds_data_restuls.csv'))</pre>
ploidy <- read.csv(paste0(mydir, '/pic_list_with_ploidy.csv'))</pre>
# Merge files
mydata2 <- merge(ploidy, mydata1)</pre>
colnames(mydata2)[1] <- "Accession"</pre>
# Keep seed with area values around the median
mydata3 <- group_by(mydata2, Accession) %>%
  filter(Area > quantile(Area, 0.45)) %>% filter(Area < quantile(Area, 0.55))
mydata3 <- as.data.frame(mydata3)</pre>
# Count total number of seeds per accession
# Total\_seeds \leftarrow mydata2 \%\% group\_by (Accession) \%\% summarise(n = n())
Total_seeds <- mydata3 %>% group_by (Accession) %>% summarise(n = n())
# Visualize coefficient of variation per accession
Accessions <- group_by(mydata3, Ploidy, Accession)
Accessions <- summarise(Accessions,
                         sampled_seeds = n(),
                         mean area = mean(Area, na.rm = TRUE),
```

Table 1: Coefficient of Variation

Ploidy	Accession	sampled_seeds	mean_area	sd_area	cv_area
2X	PI_109497_009	18	565.2222	83.41149	14.757292
2X	PI_115358_005	30	615.9667	62.15691	10.090954
2X	PI_189146_008	22	498.0909	57.45052	11.534144
2X	PI_206561_002	38	668.7105	52.23332	7.811050
2X	PI_234478_016	23	728.6522	274.50014	37.672315
2X	PI_234897_035	36	769.6389	89.71229	11.656413
2X	PI_237179_017	13	380.3077	59.10497	15.541355
2X	PI_249739_010	25	476.2800	81.20218	17.049252
2X	PI_250965_018	27	711.1111	41.99115	5.905005
2X	PI_251384_019	21	1397.9524	260.68630	18.647724
2X	PI_251421_037	19	683.4737	66.04407	9.663001
2X	PI_257740_036	20	605.2500	26.85218	4.436543
2X	PI_257741_006	28	679.4643	110.61461	16.279679
2X	PI_314571_011	15	553.4000	98.10111	17.726981
2X	PI_314687_026	16	667.0000	132.01212	19.791922
2X	PI_383651_003	27	449.2222	70.80707	15.762147
2X	PI_383652_004	25	511.2800	43.94269	8.594643
2X	PI_499640_020	22	742.4091	72.23484	9.729789
2X	PI_538934_023	19	447.1053	52.80772	11.811026
2X	PI_568183_033	16	522.1875	89.85931	17.208246
2X	PI_578733_034	18	604.3333	64.62380	10.693403
2X	PI_595130_032	11	542.0000	98.08262	18.096424
2X	PI_595140_014	20	453.1500	121.39465	26.789065
2X	PI_595145_031	15	678.4000	55.15407	8.130022
2X	PI_595146_030	15	641.8667	83.58389	13.022002
2X	PI_595158_029	11	523.7273	109.95189	20.994112
2X	PI_595167_028	16	541.6875	102.81032	18.979637
2X 2X	PI_595170_022	25	550.0800	93.94277	17.078019
2X	PI_595178_021 PI 618972 024	19 22	486.1053	115.25040 66.78232	23.708939
2X	PI018972024 PI618975025	21	$626.4545 \\ 649.2381$	94.28728	$10.660362 \\ 14.522758$
2X 2X	PI 634303 027	18	625.3889	90.75056	14.522756
2X 2X	PI 634304 013	17	470.2941	77.09553	16.393046
2X 2X	PI 636567 012	26	694.5385	49.77649	7.166844
2X 2X	PI 655206 015	25 25	725.8000	76.03234	10.475660
4X	PI_227362_045	20	945.5000	50.45842	5.336692
4X 4X	PI 227507 047	18	1056.2778	85.33243	8.078598
4X 4X	PI 229453 042	16	1082.5000	77.83658	7.190446
4X 4X	PI 229497 046	18	1032.3000 1074.2222	42.88638	3.992319
4X 4X	PI 229502 041	16	1014.2222	167.57242	16.552406
4X 4X	PI 234758 043	20	1209.3000	66.74074	5.518956
4X 4X	PI 234895 053	18	794.9444	140.98705	17.735460
4X 4X	PI_237708_039	16	794.9444 765.3125	65.42754	8.549127
4X 4X	PI 251125 052	22	938.9545	70.65306	7.524652
4X 4X	PI 251131 068	10	703.5000	239.12352	33.990549
4Λ	11_201101_008	10	703.3000	Z39.1Z33Z	33.990049

Ploidy	Accession	sampled_seeds	mean_area	sd_area	cv_area
4X	PI 287541 065	14	860.7857	99.71203	11.583839
4X	PI_302898_064	10	949.1000	101.53429	10.697954
4X	PI_302900_063	16	612.8125	209.10578	34.122311
4X	PI_312453_051	16	1272.7500	98.88074	7.769062
4X	PI_316249_044	20	692.8000	211.79822	30.571336
4X	PI_340103_054	15	749.1333	60.91665	8.131616
4X	PI_383650_049	20	685.7000	137.87336	20.106950
4X	PI_383653_038	24	718.6250	80.58688	11.214037
4X	PI_383654_048	15	547.4000	126.66198	23.138835
4X	PI_384860_050	16	800.5000	250.27718	31.265107
4X	PI_577098_066	18	644.1667	100.98296	15.676527
4X	PI_577099_067	20	675.3000	124.38061	18.418571
4X	PI_595049_062	22	867.0455	67.17956	7.748101
4X	PI_595050_061	17	867.0000	55.64396	6.417988
4X	PI_595051_055	14	940.1429	101.15324	10.759348
4X	PI_595059_060	14	806.8571	53.36645	6.614114
4X	PI_595060_059	23	740.0435	116.79449	15.782112
4X	PI_595061_058	20	779.4000	84.74072	10.872558
4X	PI_595062_057	19	824.3684	85.11770	10.325202
4X	PI_595063_056	19	866.7368	64.86554	7.483879
4X	PI_634302_040	24	651.2917	77.84794	11.952855
5X	PI_234751_087	22	1020.7273	62.81809	6.154248
5X	PI_251126_085	18	867.8889	108.96890	12.555628
5X	PI_274619_086	16	1310.9375	482.72897	36.823188
5X	PI_311405_089	16	877.8125	101.97269	11.616682
5X	PI_314522_090	16	895.1875	76.99023	8.600459
5X	PI_314523_084	15	1121.2000	103.32280	9.215376
5X	PI_315448_083	14	1011.0714	64.16381	6.346120
5X	PI_371896_082	10	1189.5000	70.12093	5.894992
5X	PI_380850_088	14	1031.2143	90.81018	8.806141
5X	PI_538933_092	15	1104.4000	95.76519	8.671241
6X	PI_229456_070	19	1038.5263	103.93340	10.007777
6X	PI_229533_073	20	1203.5500	125.84890	10.456474
6X	PI_230247_079	21	1288.3333	77.41985	6.009303
6X	PI_250967_075	22	1068.7727	74.89035	7.007136
6X	PI_251385_072	22	1030.5909	106.43785	10.327846
6X	PI_380849_078	20	921.4500	62.20973	6.751286
6X	PI_380852_076	13	838.0769	115.58724	13.791961
6X	PI_380853_071	15	926.5333	55.37775	5.976876
6X	PI_380854_069	15	865.2667	52.24320	6.037815
6X	PI_380855_077	20	1019.9500	46.79347	4.587820
6X	PI_380857_074	25	974.0400	66.73298	6.851153
6X	PI_384861_081	14	1054.4286	62.98561	5.973435
6X	PI_537103_080	17	930.0588	118.10719	12.698895
8X	PI_234750_094	13	1616.3846	74.06027	4.581847
8X	PI_318989_093	10	1591.1000	89.61455	5.632238

Convert pixels to milimiters

Now we must convert seed dimensions in pixels to mm! We used this website (https://www.pixelcalculator. com/) to get the conversion factors from px to mm.

```
## Convert px to mm
# Original Width (or length) = 2169 px (92mm)
W_px <- 2169
W_mm <- 92
# Original Height = 1987 px (84mm)
H_px <- 1987
H_mm <- 84
# 600 dpi

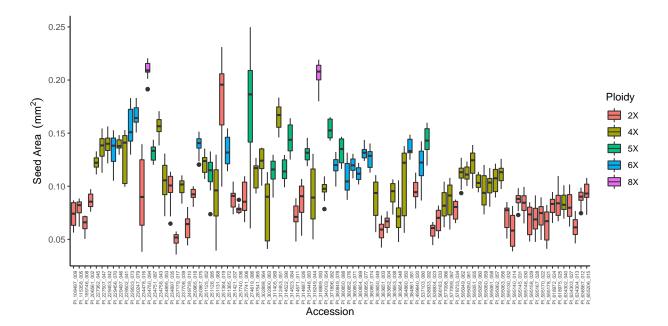
px2mm <- 0.5 * ( (W_px/W_mm) + (H_px/H_mm) ) # Average of both dimensions

# Apply conversion factors
mydata3$Area <- mydata3$Area/ (W_mm*H_mm)
mydata3$Length <- mydata3$Length / px2mm
mydata3$Width <- mydata3$Width / px2mm</pre>
```

Data visualization and analyses of variance

Seed area

```
# Distribution of the seed area across accessions
bp1 <- ggplot(mydata3, aes(x=Accession, y=Area, fill = Ploidy)) +
    geom_boxplot() +
    theme_classic() +
    theme(axis.text.x = element_text(angle = 90, size = 5)) +
    labs(y= expression(paste("Seed Area ", (mm^2))), x = "Accession")
bp1</pre>
```



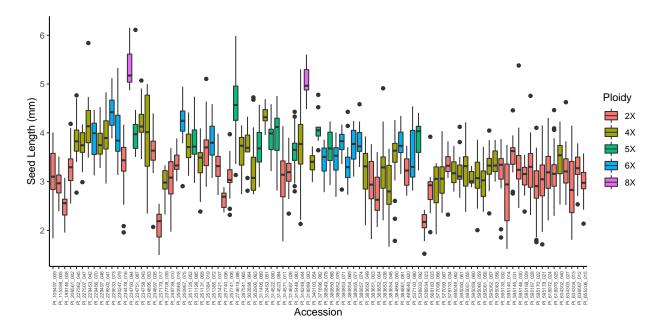
```
# Model1 <- lm(Area ~ Ploidy + Accession, data = mydata3)</pre>
Model1 <- lm(Area ~ Ploidy, data = mydata3)
summary(Model1)
##
## Call:
## lm(formula = Area ~ Ploidy, data = mydata3)
##
## Residuals:
##
        Min
                  1Q
                        Median
                                     3Q
                                             Max
## -0.073489 -0.014611 -0.001362 0.011504 0.150069
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 0.0809094 0.0009169 88.24
                                          <2e-16 ***
## Ploidy4X 0.0277244 0.0014037 19.75
                                          <2e-16 ***
## Ploidy5X
             0.0528798  0.0021962  24.08  <2e-16 ***
                                          <2e-16 ***
## Ploidy6X
             0.0514552 0.0018432 27.92
## Ploidy8X
             ## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.02493 on 1706 degrees of freedom
## Multiple R-squared: 0.4822, Adjusted R-squared: 0.481
## F-statistic: 397.2 on 4 and 1706 DF, p-value: < 2.2e-16
```

kable((anova((Model1))
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	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Ploidy	4	0.9870738	0.2467684	397.19	0
Residuals	1706	1.0599133	0.0006213	NA	NA
\					
\					

Seed length

```
# Distribution of the seed length across accessions
bp2 <- ggplot(mydata3, aes(x=Accession, y=Length, fill = Ploidy)) +
    geom_boxplot() +
    theme_classic() +
    theme(axis.text.x = element_text(angle = 90, size = 5)) +
    labs(y= "Seed Length (mm)", x = "Accession")</pre>
bp2
```



```
# Regress the seed length on ploidy level
Model2 <- lm(Length ~ Ploidy, data = mydata3)
summary(Model2)</pre>
```

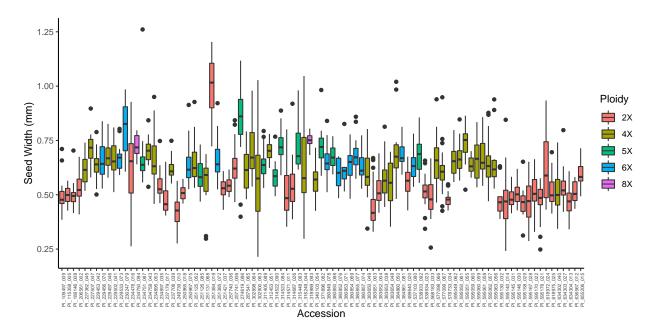
```
##
## Call:
## lm(formula = Length ~ Ploidy, data = mydata3)
##
## Residuals:
       Min
##
                 1Q
                      Median
                                           Max
## -1.79906 -0.37155 0.00707 0.35580 2.37514
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 3.09412
                          0.02072 149.30
                                            <2e-16 ***
                          0.03173
                                   11.66
## Ploidy4X
               0.37008
## Ploidy5X
               0.84633
                          0.04964
                                    17.05
                                            <2e-16 ***
               0.72059
                                    17.30
## Ploidy6X
                          0.04166
                                            <2e-16 ***
## Ploidy8X
               2.13010
                          0.11928
                                    17.86
                                            <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.5634 on 1706 degrees of freedom
## Multiple R-squared: 0.3022, Adjusted R-squared: 0.3006
## F-statistic: 184.7 on 4 and 1706 DF, p-value: < 2.2e-16
```

kable(anova(Model2))

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Ploidy	4	234.5362	58.6340528	184.7414	0
Residuals	1706	541.4581	0.3173846	NA	NA

Seed width

```
# Distribution of the seed width across accessions
bp3 <- ggplot(mydata3, aes(x=Accession, y=Width, fill = Ploidy)) +
   geom_boxplot() +
   theme_classic() +
   theme(axis.text.x = element_text(angle = 90, size = 5)) +
   labs(y= "Seed Width (mm)", x = "Accession")</pre>
bp3
```



```
# Regress the seed width using a Type II ANOVA (main effects)
Model3 <- lm(Width ~ Ploidy, data = mydata3)
summary(Model3)</pre>
```

```
##
## Call:
## lm(formula = Width ~ Ploidy, data = mydata3)
##
## Residuals:
##
       Min
                  1Q
                       Median
                                    3Q
                                            Max
## -0.42185 -0.06683 -0.01546 0.04814 0.67156
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.531867
                          0.004308
                                   123.47 < 2e-16 ***
## Ploidy4X
               0.104193
                          0.006595
                                     15.80 < 2e-16 ***
## Ploidy5X
                          0.010318
                                     14.51 < 2e-16 ***
               0.149710
## Ploidy6X
               0.129977
                          0.008660
                                     15.01 < 2e-16 ***
## Ploidy8X
               0.203081
                          0.024795
                                     8.19 5.05e-16 ***
## ---
```

```
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1171 on 1706 degrees of freedom
## Multiple R-squared: 0.2183, Adjusted R-squared: 0.2164
## F-statistic: 119.1 on 4 and 1706 DF, p-value: < 2.2e-16</pre>
```

kable(anova(Model3))

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Ploidy	4	6.532024	1.6330059	119.0769	0
Residuals	1706	23.395865	0.0137139	NA	NA

Results

Our results indicate that there are statistical differences in seed area, length and width between four different ploidy levels of Festuca at the $\alpha = 5$.

Notes

- Please read the methods.
- These results coincide with the previous results.
- Some accession has more variability than other, do you want to keep them all? Look at the plots and let me know if there is any accession you want to remove or include.
- I did not scan the "controls" we used before because I did not have them.
- The Github repository has been updated. I would only talk about the latest Python code in the methods and would not mentioned the Matlab one.
- Let me know if there are some questions or concerns

References

R Core Team (2014). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/

Wickham, H. (2009) ggplot2: elegant graphics for data analysis. Springer New York.