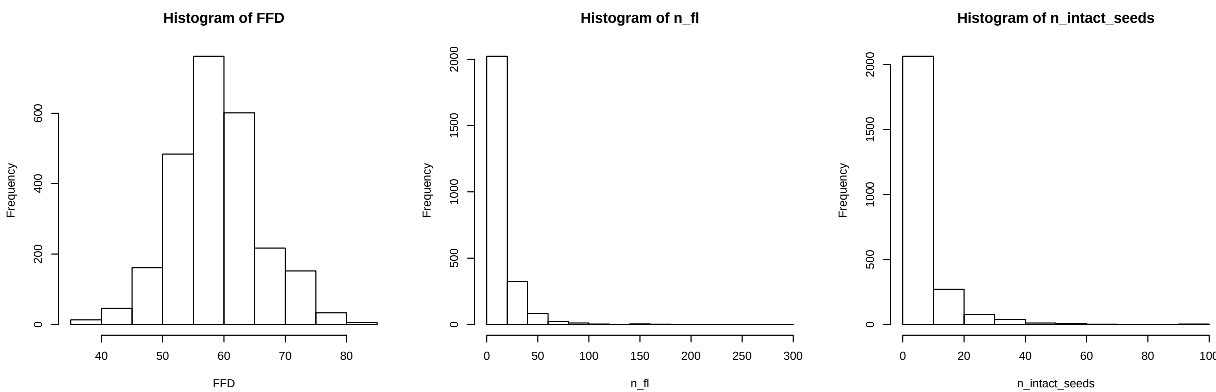
Yearly selection models Lathyrus

Contents

Select data and look at variables

```
data_sel<-subset(alldata_weather_subs,!is.na(n_fl)&!is.na(FFD))
#Select data where both FFD and n_fl are available
nrow(subset(data_sel,is.na(n_intact_seeds))) #No NAs for seed data
```

```
## [1] 0
```



Calculation of relative fitness and standardized traits

Relativization and standardization was done within each year.

```
data_sel<-data.frame(
  data_sel %>%
  group_by(year) %>%
  mutate(n_intact_seeds_rel=n_intact_seeds/mean(n_intact_seeds)) %>% #Relative fitness
  mutate(FFD_std=(FFD-mean(FFD))/sd(FFD)) %>%                        #Standardized FFD
  mutate(n_fl_std=(n_fl-mean(n_fl))/sd(n_fl)))                       #Standardized n_fl
```

Phenotypic selection models with all data

```
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:year, data = data_sel),type="II")
```

```
## Anova Table (Type II tests)
##
## Response: n_intact_seeds_rel
##               Sum Sq   Df  F value  Pr(>F)
## FFD_std        446.8    1 107.6082 < 2e-16 ***
## FFD_std:year   147.4   21   1.6906 0.02561 *
## Residuals    10177.0 2451
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Not sure about type - II for interactions?
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:year+n_fl_std,
         data = data_sel),type="II")
```

```
## Anova Table (Type II tests)
##
## Response: n_intact_seeds_rel
##              Sum Sq   Df F value    Pr(>F)
## FFD_std       121.7    1 30.1748 4.355e-08 ***
## n_fl_std      294.1    1 72.9143 < 2.2e-16 ***
## FFD_std:year  147.4   21  1.7404   0.01961 *
## Residuals    9882.9 2450
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Selection for early flowering differs among years when considering only FFD
#and also when including number of flowers as a covariate

Anova(update(lm(n_intact_seeds_rel ~ (FFD_std+I(FFD_std^2))*year,
                data = data_sel),.~.-year),type="II")
```

```
## Anova Table (Type II tests)
##
## Response: n_intact_seeds_rel
##                    Sum Sq   Df  F value    Pr(>F)
## FFD_std             431.0    1 103.5358 < 2.2e-16 ***
## I(FFD_std^2)          5.2    1   1.2381  0.265939
## FFD_std:year        167.7   21   1.9179  0.007227 **
## I(FFD_std^2):year    61.0   21   0.6982  0.838871
## Residuals         10110.8 2429
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Anova(update(lm(n_intact_seeds_rel~(FFD_std+I(FFD_std^2))*year+
                  FFD_std:n_fl_std+n_fl_std+I(n_fl_std^2), data = data_sel),.~.-year),type="II")
```

```
## Anova Table (Type II tests)
##
## Response: n_intact_seeds_rel
##                   Sum Sq   Df F value    Pr(>F)
## FFD_std             77.7    1 19.2492 1.196e-05 ***
## I(FFD_std^2)         3.1    1  0.7671  0.381194
## n_fl_std           228.5    1 56.6087 7.446e-14 ***
## I(n_fl_std^2)       21.0    1  5.2013  0.022657 *
## FFD_std:year       163.0   21  1.9223  0.007046 **
## I(FFD_std^2):year   52.0   21  0.6138  0.911903
## FFD_std:n_fl_std     1.6    1  0.4019  0.526176
## Residuals         9794.4 2426
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#No evidence of non-linear selection for FFD (but quadratic selection for n_fl)
```

Phenotypic selection models for each year

With only FFD

```
sel_models1<-data_sel %>%
  group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std, data = .))
sel_models1_coefs<-data.frame(sel_models1 %>% tidy(model))
sel_models1_coefs$sig<-ifelse(sel_models1_coefs$p.value<0.05,"*","")
sel_models1_rsq<-data.frame(sel_models1 %>% glance(model))[1:3]
sel_models1_anova<-cbind(
  year=c("1987","1988","1989","1990","1991","1992","1993","1994","1995","1996","2006",
         "2007","2008","2009","2010","2011","2012","2013","2014","2015","2016","2017"),
  variable=rep(c("FFD_std"),22),
   plyr::ldply(lapply(as.list(sel_models1)$model,FUN=Anova), function(x) data.frame(x)[1,3:4]))
sel_models1_anova$sig<-ifelse(sel_models1_anova$Pr..F.<0.05,"*","")
kable(sel_models1_coefs)  #Selection gradients
```

year	term	estimate	std.error	statistic	p.value	sig
1987	(Intercept)	1.0000000	0.0915849	10.9188251	0.0000000	*
1987	FFD_std	-0.3719280	0.0917780	-4.0524759	0.0000688	*
1988	(Intercept)	1.0000000	0.1060225	9.4319627	0.0000000	*
1988	FFD_std	-0.3019653	0.1063338	-2.8397850	0.0050689	*
1989	(Intercept)	1.0000000	0.1270571	7.8704777	0.0000000	*
1989	FFD_std	-0.6087614	0.1277103	-4.7667351	0.0000067	*
1990	(Intercept)	1.0000000	0.1616679	6.1855183	0.0000000	*
1990	FFD_std	-0.4685032	0.1622792	-2.8870199	0.0045508	*
1991	(Intercept)	1.0000000	0.0777087	12.8685776	0.0000000	*
1991	FFD_std	-0.6619568	0.0779254	-8.4947476	0.0000000	*
1992	(Intercept)	1.0000000	0.1823773	5.4831399	0.0000003	*
1992	FFD_std	-0.4378889	0.1831685	-2.3906346	0.0184576	*
1993	(Intercept)	1.0000000	0.1323285	7.5569497	0.0000000	*
1993	FFD_std	-0.4282364	0.1327039	-3.2270062	0.0014934	*
1994	(Intercept)	1.0000000	0.1794638	5.5721557	0.0000001	*
1994	FFD_std	-0.4294513	0.1799455	-2.3865627	0.0180153	*
1995	(Intercept)	1.0000000	0.2385668	4.1916978	0.0001486	*
1995	FFD_std	-0.1465151	0.2414586	-0.6067919	0.5474180	
1996	(Intercept)	1.0000000	0.1058594	9.4464959	0.0000000	*
1996	FFD_std	-0.3733017	0.1062888	-3.5121447	0.0006240	*
2006	(Intercept)	1.0000000	0.1347269	7.4224224	0.0000000	*
2006	FFD_std	-0.3955237	0.1354493	-2.9200863	0.0044004	*
2007	(Intercept)	1.0000000	0.1101048	9.0822593	0.0000000	*
2007	FFD_std	-0.4249668	0.1106951	-3.8390741	0.0002265	*
2008	(Intercept)	1.0000000	0.1198591	8.3431268	0.0000000	*
2008	FFD_std	-0.5121975	0.1206059	-4.2468684	0.0000587	*
2009	(Intercept)	1.0000000	0.2663471	3.7544998	0.0003993	*
2009	FFD_std	-0.2149129	0.2685574	-0.8002494	0.4267769	
2010	(Intercept)	1.0000000	0.1624538	6.1555960	0.0000000	*
2010	FFD_std	-0.4919611	0.1635627	-3.0077827	0.0036234	*
2011	(Intercept)	1.0000000	0.1951871	5.1232899	0.0000019	*
2011	FFD_std	-0.7085164	0.1963319	-3.6087691	0.0005218	*
2012	(Intercept)	1.0000000	0.1862022	5.3705053	0.0000005	*

year	term	estimate	std.error	statistic	p.value	sig
2012	FFD_std	-1.0347981	0.1870544	-5.5320699	0.0000002	*
2013	(Intercept)	1.0000000	0.3200235	3.1247708	0.0026297	*
2013	FFD_std	-0.4252879	0.3223680	-1.3192622	0.1915723	
2014	(Intercept)	1.0000000	0.1719726	5.8148792	0.0000002	*
2014	FFD_std	-0.6681021	0.1733539	-3.8539771	0.0002819	*
2015	(Intercept)	1.0000000	0.2280947	4.3841449	0.0001063	*
2015	FFD_std	0.0480660	0.2313302	0.2077810	0.8366396	
2016	(Intercept)	1.0000000	0.0953638	10.4861559	0.0000000	*
2016	FFD_std	-0.3509882	0.0957963	-3.6639005	0.0003853	*
2017	(Intercept)	1.0000000	0.4954213	2.0184842	0.0456470	*
2017	FFD_std	0.2817863	0.4973527	0.5665723	0.5720047	

```
#FFD * (selection for early flowering) in all years but 1995,2009,2013,2015,2017
kable(sel_models1_rsq) #R squares
```

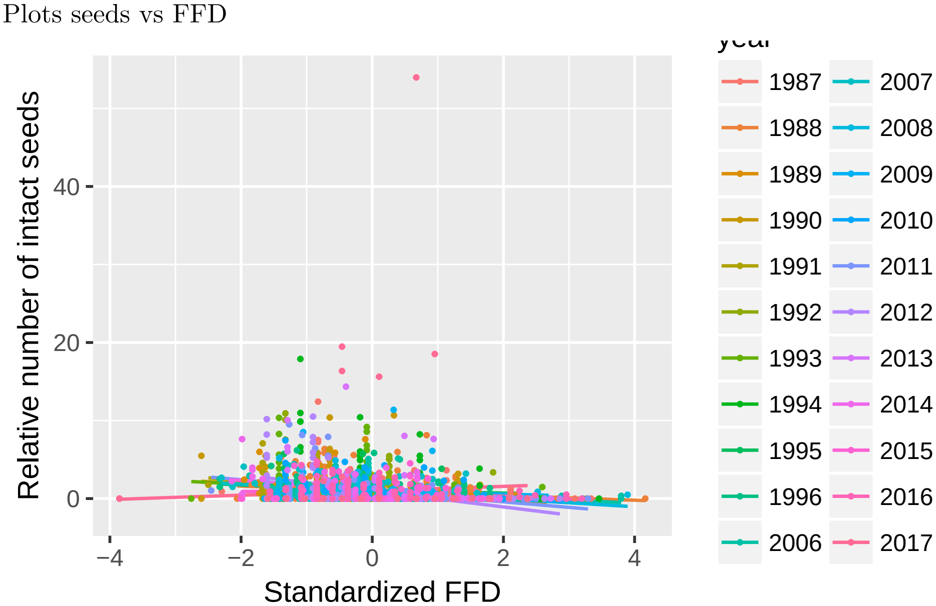
year	r.squared	adj.r.squared
1987	0.0650598	0.0610982
1988	0.0455449	0.0398972
1989	0.1913867	0.1829636
1990	0.0598191	0.0526421
1991	0.2884575	0.2844601
1992	0.0477394	0.0393863
1993	0.0561640	0.0507707
1994	0.0298679	0.0246240
1995	0.0091210	-0.0156510
1996	0.0918238	0.0843797
2006	0.0848221	0.0748745
2007	0.1380804	0.1287117
2008	0.1858683	0.1755628
2009	0.0107377	-0.0060295
2010	0.1116239	0.0992854
2011	0.1342278	0.1239210
2012	0.2208006	0.2135858
2013	0.0253192	0.0107717
2014	0.1958144	0.1826311
2015	0.0012682	-0.0281063
2016	0.1096529	0.1014846
2017	0.0025212	-0.0053329

```
kable(sel_models1_anova) #Anova results
```

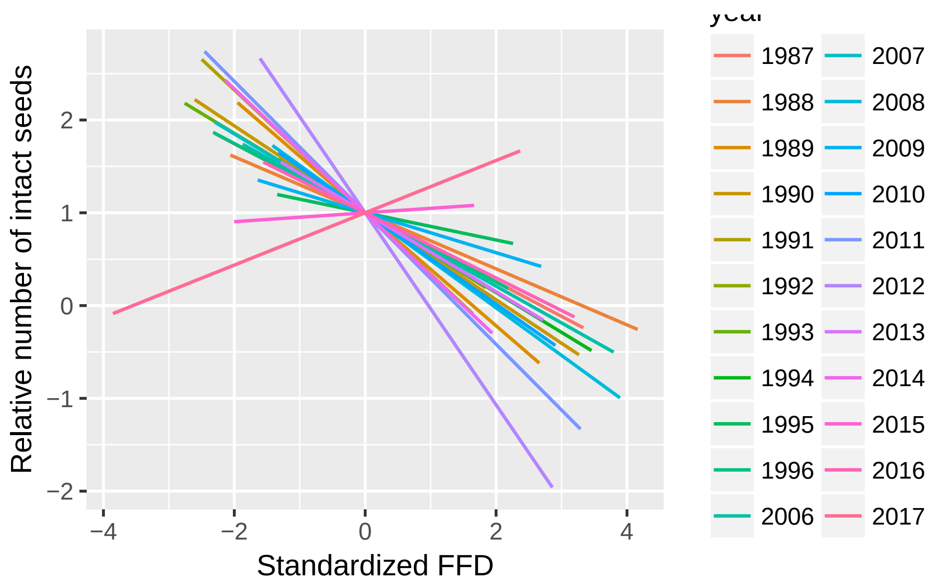
year	variable	F.value	Pr..F.	sig
1987	FFD_std	16.4225607	0.0000688	*
1988	FFD_std	8.0643789	0.0050689	*
1989	FFD_std	22.7217636	0.0000067	*
1990	FFD_std	8.3348839	0.0045508	*
1991	FFD_std	72.1607366	0.0000000	*
1992	FFD_std	5.7151338	0.0184576	*
1993	FFD_std	10.4135689	0.0014934	*

year	variable	F.value	Pr..F.	sig
1994	FFD_std	5.6956815	0.0180153	*
1995	FFD_std	0.3681964	0.5474180	
1996	FFD_std	12.3351607	0.0006240	*
2006	FFD_std	8.5269038	0.0044004	*
2007	FFD_std	14.7384898	0.0002265	*
2008	FFD_std	18.0358916	0.0000587	*
2009	FFD_std	0.6403990	0.4267769	
2010	FFD_std	9.0467567	0.0036234	*
2011	FFD_std	13.0232146	0.0005218	*
2012	FFD_std	30.6037971	0.0000002	*
2013	FFD_std	1.7404528	0.1915723	
2014	FFD_std	14.8531392	0.0002819	*
2015	FFD_std	0.0431729	0.8366396	
2016	FFD_std	13.4241668	0.0003853	*
2017	FFD_std	0.3210042	0.5720047	

Plots seeds vs FFD



Same plot but with only the fit lines (no data points)



There is one outlier in 2017 with a very high relative number of intact seeds. This is a correct value (the plant had 9 intact seeds but the relative value is so high because only 7 plants produced seeds in 2017, so the mean for that year is very low). I think this value is driving the pattern for 2017 (year with the most positive slope in the previous graph).

With FFD & number of flowers

```
sel_models2<-as.list(data_sel %>%
  group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std+n_fl_std, data = .)) )
sel_models2<-data_sel %>%
  group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std+n_fl_std, data = .))
sel_models2_coefs<-data.frame(sel_models2 %>% tidy(model))
sel_models2_coefs$sig<-ifelse(sel_models2_coefs$p.value<0.05,"*","")
sel_models2_rsq<-data.frame(sel_models2 %>% glance(model))[1:3]
sel_models2_anova<-cbind(
  year=c("1987","1987","1988","1988","1989","1989","1990","1990","1991","1991",
  "1992","1992","1993","1993","1994","1994","1995","1995","1996","1996","2006",
  "2006","2007","2007","2008","2008","2009","2009","2010","2010","2011","2011",
  "2012","2012","2013","2013","2014","2014","2015","2015","2016","2016",
  "2017","2017"),variable=rep(c("FFD_std","n_fl_std"),22),
   plyr::ldply(lapply(as.list(sel_models2)$model,FUN=Anova),
   function(x) data.frame(x)[1:2,3:4]))
sel_models2_anova$sig<-ifelse(sel_models2_anova$Pr..F.<0.05,"*","")

kable(sel_models2_coefs) #Selection gradients
```

year	term	estimate	std.error	statistic	p.value	sig
1987	(Intercept)	1.0000000	0.0806475	12.3996342	0.0000000	*
1987	FFD_std	-0.0779057	0.0881928	-0.8833567	0.3779463	
1987	n_fl_std	0.7344574	0.0881928	8.3278594	0.0000000	*
1988	(Intercept)	1.0000000	0.1003991	9.9602439	0.0000000	*

year	term	estimate	std.error	statistic	p.value	sig
1988	FFD_std	-0.0878159	0.1112680	-0.7892286	0.4310908	
1988	n_fl_std	0.5033133	0.1112680	4.5234322	0.0000115	*
1989	(Intercept)	1.0000000	0.1121671	8.9152722	0.0000000	*
1989	FFD_std	-0.1441208	0.1427321	-1.0097295	0.3151898	
1989	n_fl_std	0.7576835	0.1427321	5.3084320	0.0000007	*
1990	(Intercept)	1.0000000	0.1552273	6.4421661	0.0000000	*
1990	FFD_std	-0.2398513	0.1691158	-1.4182663	0.1585058	
1990	n_fl_std	0.5881817	0.1691158	3.4779815	0.0006877	*
1991	(Intercept)	1.0000000	0.0721812	13.8540252	0.0000000	*
1991	FFD_std	-0.3982279	0.0872502	-4.5642040	0.0000094	*
1991	n_fl_std	0.4723255	0.0872502	5.4134579	0.0000002	*
1992	(Intercept)	1.0000000	0.1830969	5.4615893	0.0000003	*
1992	FFD_std	-0.4628387	0.1992692	-2.3226800	0.0219866	*
1992	n_fl_std	-0.0647689	0.1992692	-0.3250319	0.7457579	
1993	(Intercept)	1.0000000	0.1309488	7.6365702	0.0000000	*
1993	FFD_std	-0.3000375	0.1440021	-2.0835636	0.0386613	*
1993	n_fl_std	0.3124230	0.1440021	2.1695728	0.0313955	*
1994	(Intercept)	1.0000000	0.1785389	5.6010190	0.0000001	*
1994	FFD_std	-0.3002982	0.1943117	-1.5454456	0.1239567	
1994	n_fl_std	0.3321273	0.1943117	1.7092501	0.0890906	
1995	(Intercept)	1.0000000	0.2357703	4.2414168	0.0001322	*
1995	FFD_std	0.0183948	0.2661905	0.0691037	0.9452601	
1995	n_fl_std	0.3721466	0.2661905	1.3980463	0.1700002	
1996	(Intercept)	1.0000000	0.0940797	10.6292883	0.0000000	*
1996	FFD_std	-0.1697922	0.1007997	-1.6844507	0.0946724	
1996	n_fl_std	0.5831053	0.1007997	5.7847908	0.0000001	*
2006	(Intercept)	1.0000000	0.1244082	8.0380562	0.0000000	*
2006	FFD_std	-0.2280061	0.1315479	-1.7332548	0.0864376	
2006	n_fl_std	0.5406975	0.1315479	4.1102699	0.0000864	*
2007	(Intercept)	1.0000000	0.1104844	9.0510499	0.0000000	*
2007	FFD_std	-0.3827784	0.1310118	-2.9217097	0.0043900	*
2007	n_fl_std	0.0795626	0.1310118	0.6072935	0.5451685	
2008	(Intercept)	1.0000000	0.0997242	10.0276525	0.0000000	*
2008	FFD_std	-0.2102002	0.1122235	-1.8730500	0.0648080	
2008	n_fl_std	0.6744773	0.1122235	6.0101270	0.0000001	*
2009	(Intercept)	1.0000000	0.2670647	3.7444103	0.0004176	*
2009	FFD_std	-0.0700757	0.3212662	-0.2181236	0.8280984	
2009	n_fl_std	0.2655695	0.3212662	0.8266336	0.4118326	
2010	(Intercept)	1.0000000	0.1635740	6.1134396	0.0000000	*
2010	FFD_std	-0.4783838	0.1945310	-2.4591648	0.0163648	*
2010	n_fl_std	0.0255105	0.1945310	0.1311384	0.8960367	
2011	(Intercept)	1.0000000	0.1832996	5.4555485	0.0000005	*
2011	FFD_std	-0.3007029	0.2181104	-1.3786732	0.1717001	
2011	n_fl_std	0.7633405	0.2181104	3.4997897	0.0007516	*
2012	(Intercept)	1.0000000	0.1778849	5.6216126	0.0000002	*
2012	FFD_std	-0.6654602	0.2096835	-3.1736409	0.0019658	*
2012	n_fl_std	0.7059695	0.2096835	3.3668334	0.0010572	*
2013	(Intercept)	1.0000000	0.3224387	3.1013643	0.0028330	*
2013	FFD_std	-0.4255495	0.3313975	-1.2841059	0.2035944	
2013	n_fl_std	-0.0013175	0.3313975	-0.0039755	0.9968400	
2014	(Intercept)	1.0000000	0.1722283	5.8062475	0.0000003	*
2014	FFD_std	-0.7773420	0.2114498	-3.6762488	0.0005072	*

year	term	estimate	std.error	statistic	p.value	sig
2014	n_fl_std	-0.1913632	0.2114498	-0.9050057	0.3690821	
2015	(Intercept)	1.0000000	0.2314274	4.3210095	0.0001341	*
2015	FFD_std	0.0830019	0.3146461	0.2637946	0.7935785	
2015	n_fl_std	0.0524562	0.3146461	0.1667149	0.8686117	
2016	(Intercept)	1.0000000	0.0832130	12.0173594	0.0000000	*
2016	FFD_std	-0.0547893	0.0973799	-0.5626342	0.5748500	
2016	n_fl_std	0.5773963	0.0973799	5.9293167	0.0000000	*
2017	(Intercept)	1.0000000	0.4956903	2.0173886	0.0457795	*
2017	FFD_std	-0.0204262	0.5946111	-0.0343521	0.9726507	
2017	n_fl_std	-0.5521131	0.5946111	-0.9285281	0.3549091	

```
#FFD * (selection for early flowering) in 1991,1992,1993,2007,2010,2012,2014
kable(sel_models2_rsq) #R squares
```

year	r.squared	adj.r.squared
1987	0.2781054	0.2719617
1988	0.1491710	0.1390421
1989	0.3763711	0.3632421
1990	0.1398546	0.1266216
1991	0.3895315	0.3826335
1992	0.0486289	0.0317905
1993	0.0810241	0.0704612
1994	0.0450308	0.0346507
1995	0.0564101	0.0080209
1996	0.2885756	0.2768165
2006	0.2281226	0.2111582
2007	0.1415595	0.1226926
2008	0.4435562	0.4292884
2009	0.0222569	-0.0114584
2010	0.1118390	0.0868204
2011	0.2455622	0.2273830
2012	0.2954414	0.2822721
2013	0.0253194	-0.0042163
2014	0.2066442	0.1801990
2015	0.0021086	-0.0583696
2016	0.3283065	0.3158678
2017	0.0093002	-0.0064252

```
kable(sel_models2_anova) #Anova results
```

year	variable	F.value	Pr..F.	sig
1987	FFD_std	0.7803191	0.3779463	
1987	n_fl_std	69.3532416	0.0000000	*
1988	FFD_std	0.6228818	0.4310908	
1988	n_fl_std	20.4614387	0.0000115	*
1989	FFD_std	1.0195537	0.3151898	
1989	n_fl_std	28.1794505	0.0000007	*
1990	FFD_std	2.0114792	0.1585058	
1990	n_fl_std	12.0963551	0.0006877	*

year	variable	F.value	Pr..F.	sig
1991	FFD_std	20.8319581	0.0000094	*
1991	n_fl_std	29.3055260	0.0000002	*
1992	FFD_std	5.3948425	0.0219866	*
1992	n_fl_std	0.1056457	0.7457579	
1993	FFD_std	4.3412374	0.0386613	*
1993	n_fl_std	4.7070460	0.0313955	*
1994	FFD_std	2.3884021	0.1239567	
1994	n_fl_std	2.9215359	0.0890906	
1995	FFD_std	0.0047753	0.9452601	
1995	n_fl_std	1.9545335	0.1700002	
1996	FFD_std	2.8373741	0.0946724	
1996	n_fl_std	33.4638045	0.0000001	*
2006	FFD_std	3.0041723	0.0864376	
2006	n_fl_std	16.8943186	0.0000864	*
2007	FFD_std	8.5363875	0.0043900	*
2007	n_fl_std	0.3688054	0.5451685	
2008	FFD_std	3.5083162	0.0648080	
2008	n_fl_std	36.1216265	0.0000001	*
2009	FFD_std	0.0475779	0.8280984	
2009	n_fl_std	0.6833231	0.4118326	
2010	FFD_std	6.0474915	0.0163648	*
2010	n_fl_std	0.0171973	0.8960367	
2011	FFD_std	1.9007397	0.1717001	
2011	n_fl_std	12.2485281	0.0007516	*
2012	FFD_std	10.0719969	0.0019658	*
2012	n_fl_std	11.3355669	0.0010572	*
2013	FFD_std	1.6489280	0.2035944	
2013	n_fl_std	0.0000158	0.9968400	
2014	FFD_std	13.5148054	0.0005072	*
2014	n_fl_std	0.8190353	0.3690821	
2015	FFD_std	0.0695876	0.7935785	
2015	n_fl_std	0.0277939	0.8686117	
2016	FFD_std	0.3165572	0.5748500	
2016	n_fl_std	35.1567971	0.0000000	*
2017	FFD_std	0.0011801	0.9726507	
2017	n_fl_std	0.8621644	0.3549091	

```r
sel_grads_FFD<-subset(sel_models2_coefs,term=="FFD_std")[c(1,3,7)]
sel_grads_FFD
```

```
##    year    estimate sig
## 2  1987 -0.07790572
## 5  1988 -0.08781589
## 8  1989 -0.14412079
## 11 1990 -0.23985125
## 14 1991 -0.39822789   *
## 17 1992 -0.46283867   *
## 20 1993 -0.30003746   *
## 23 1994 -0.30029817
## 26 1995  0.01839476
## 29 1996 -0.16979216
## 32 2006 -0.22800610
```

```
## 35 2007 -0.38277840   *
## 38 2008 -0.21020015
## 41 2009 -0.07007575
## 44 2010 -0.47838381   *
## 47 2011 -0.30070294
## 50 2012 -0.66546024   *
## 53 2013 -0.42554949
## 56 2014 -0.77734197   *
## 59 2015  0.08300195
## 62 2016 -0.05478926
## 65 2017 -0.02042616
```

```
#These are the per-year selection gradients for FFD, to be used in further analyses
```

Non-linear selection (with FFD & number of flowers)

```
sel_models3<-data_sel %>%
  group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std+I(FFD_std^2)+n_fl_std+I(n_fl_std^2)+
                FFD_std:n_fl_std, data = .))
sel_models3_coefs<-data.frame(sel_models3 %>% tidy(model))
sel_models3_coefs$sig<-ifelse(sel_models3_coefs$p.value<0.05,"*","")
sel_models3_rsq<-data.frame(sel_models3 %>% glance(model))[1:3]
sel_models3_anova<-cbind(
  year=c("1987","1987","1987","1987","1987","1988","1988","1988","1988","1988",
         "1989","1989","1989","1989","1989","1990","1990","1990","1990","1990",
         "1991","1991","1991","1991","1991","1992","1992","1992","1992","1992",
         "1993","1993","1993","1993","1993","1994","1994","1994","1994","1994",
         "1995","1995","1995","1995","1995","1996","1996","1996","1996","1996",
         "2006","2006","2006","2006","2006","2007","2007","2007","2007","2007",
         "2008","2008","2008","2008","2008","2009","2009","2009","2009","2009",
         "2010","2010","2010","2010","2010","2011","2011","2011","2011","2011",
         "2012","2012","2012","2012","2012","2013","2013","2013","2013","2013",
         "2014","2014","2014","2014","2014","2015","2015","2015","2015","2015",
         "2016","2016","2016","2016","2016","2017","2017","2017","2017","2017"),
  variable=rep(c("FFD_std","I(FFD_std^2)","n_fl_std","I(n_fl_std^2)","FFD_std:n_fl_std"),22),
  plyr::ldply(lapply(as.list(sel_models3)$model,FUN=Anova), function(x) data.frame(x)[1:5,3:4]))
sel_models3_anova$sig<-ifelse(sel_models3_anova$Pr..F.<0.05,"*","")

kable(sel_models3_coefs) #Selection gradients
```

year	term	estimate	std.error	statistic	p.value	sig
1987	(Intercept)	1.0695037	0.1148860	9.3092627	0.0000000	*
1987	FFD_std	-0.0122040	0.1145872	-0.1065038	0.9152747	
1987	I(FFD_std^2)	-0.0708598	0.0847675	-0.8359316	0.4040535	
1987	n_fl_std	0.7356695	0.1482948	4.9608586	0.0000014	*
1987	I(n_fl_std^2)	0.0052502	0.0485437	0.1081547	0.9139665	
1987	FFD_std:n_fl_std	0.0104599	0.1803921	0.0579841	0.9538112	
1988	(Intercept)	1.0572781	0.1331494	7.9405426	0.0000000	*
1988	FFD_std	0.0515673	0.1247776	0.4132738	0.6799426	
1988	I(FFD_std^2)	0.0911390	0.0754437	1.2080388	0.2287610	
1988	n_fl_std	0.6410084	0.1887846	3.3954480	0.0008584	*

year	term	estimate	std.error	statistic	p.value	sig
1988	I(n_fl_std^2)	0.0971103	0.0718155	1.3522197	0.1781555	
1988	FFD_std:n_fl_std	0.5778527	0.1785712	3.2359794	0.0014650	*
1989	(Intercept)	0.9006827	0.1735238	5.1905415	0.0000012	*
1989	FFD_std	-0.1891090	0.1582507	-1.1949962	0.2351600	
1989	I(FFD_std^2)	0.0347796	0.1340940	0.2593676	0.7959311	
1989	n_fl_std	0.6328408	0.2287928	2.7659992	0.0068585	*
1989	I(n_fl_std^2)	0.1028702	0.1537660	0.6690051	0.5051675	
1989	FFD_std:n_fl_std	0.0608388	0.2245227	0.2709693	0.7870217	
1990	(Intercept)	1.1537867	0.1951793	5.9114186	0.0000000	*
1990	FFD_std	-0.1710646	0.1756620	-0.9738281	0.3319931	
1990	I(FFD_std^2)	-0.0490858	0.1196485	-0.4102502	0.6823137	
1990	n_fl_std	1.0279019	0.2522100	4.0755789	0.0000804	*
1990	I(n_fl_std^2)	-0.2426828	0.0761838	-3.1854904	0.0018185	*
1990	FFD_std:n_fl_std	-0.3519460	0.2784606	-1.2638985	0.2085814	
1991	(Intercept)	0.9104917	0.1109030	8.2097993	0.0000000	*
1991	FFD_std	-0.3994336	0.0975447	-4.0948767	0.0000646	*
1991	I(FFD_std^2)	0.0386915	0.0859803	0.4500041	0.6532676	
1991	n_fl_std	0.3693223	0.1284431	2.8753774	0.0045396	*
1991	I(n_fl_std^2)	0.1195535	0.0848676	1.4087068	0.1607063	
1991	FFD_std:n_fl_std	0.1222085	0.1646138	0.7423957	0.4588486	
1992	(Intercept)	1.1696589	0.2593957	4.5091688	0.0000163	*
1992	FFD_std	-0.3235903	0.2126508	-1.5216976	0.1309544	
1992	I(FFD_std^2)	0.0963843	0.1835101	0.5252261	0.6004831	
1992	n_fl_std	0.4698371	0.3370334	1.3940370	0.1661161	
1992	I(n_fl_std^2)	-0.2013982	0.1116555	-1.8037468	0.0740080	
1992	FFD_std:n_fl_std	0.1716466	0.2521504	0.6807310	0.4974722	
1993	(Intercept)	1.0905872	0.1855686	5.8770020	0.0000000	*
1993	FFD_std	-0.2331117	0.1578170	-1.4771009	0.1414879	
1993	I(FFD_std^2)	0.0206008	0.1193892	0.1725514	0.8632081	
1993	n_fl_std	0.5008903	0.2536732	1.9745496	0.0499294	*
1993	I(n_fl_std^2)	-0.0490544	0.0902515	-0.5435296	0.5874731	
1993	FFD_std:n_fl_std	0.1526750	0.1940275	0.7868728	0.4324455	
1994	(Intercept)	1.0421161	0.2565727	4.0616789	0.0000725	*
1994	FFD_std	-0.2658891	0.2433311	-1.0927048	0.2759757	
1994	I(FFD_std^2)	-0.0177802	0.1710514	-0.1039463	0.9173270	
1994	n_fl_std	0.4383997	0.2817173	1.5561689	0.1214147	
1994	I(n_fl_std^2)	-0.0561453	0.0972931	-0.5770734	0.5646069	
1994	FFD_std:n_fl_std	-0.0812179	0.2358531	-0.3443582	0.7309767	
1995	(Intercept)	1.3459925	0.3745225	3.5938893	0.0009675	*
1995	FFD_std	0.2018072	0.3246316	0.6216499	0.5380892	
1995	I(FFD_std^2)	-0.2285683	0.3075587	-0.7431697	0.4622016	
1995	n_fl_std	0.8674691	0.5150432	1.6842645	0.1007830	
1995	I(n_fl_std^2)	-0.1940471	0.1512681	-1.2828025	0.2077592	
1995	FFD_std:n_fl_std	-0.1538687	0.4431465	-0.3472185	0.7304489	
1996	(Intercept)	1.0985275	0.1419234	7.7402844	0.0000000	*
1996	FFD_std	-0.1655069	0.1092254	-1.5152789	0.1323760	
1996	I(FFD_std^2)	-0.0488930	0.0925082	-0.5285265	0.5981267	
1996	n_fl_std	0.6834019	0.1804443	3.7873296	0.0002411	*
1996	I(n_fl_std^2)	-0.0524238	0.0789387	-0.6641082	0.5079167	
1996	FFD_std:n_fl_std	-0.0056971	0.1387211	-0.0410685	0.9673107	
2006	(Intercept)	1.1615976	0.1337477	8.6849892	0.0000000	*
2006	FFD_std	-0.1483329	0.1553453	-0.9548593	0.3422645	

year	term	estimate	std.error	statistic	p.value	sig
2006	I(FFD_std^2)	0.1130777	0.0745380	1.5170485	0.1328387	
2006	n_fl_std	1.5433766	0.2378706	6.4883020	0.0000000	*
2006	I(n_fl_std^2)	-0.1648282	0.0623970	-2.6416043	0.0097642	*
2006	FFD_std:n_fl_std	0.3601627	0.2103102	1.7125305	0.0903206	
2007	(Intercept)	0.9815732	0.1586249	6.1880146	0.0000000	*
2007	FFD_std	-0.2479242	0.1451874	-1.7076148	0.0912337	
2007	I(FFD_std^2)	0.2431026	0.1495139	1.6259532	0.1075357	
2007	n_fl_std	0.5403307	0.2698136	2.0026070	0.0482976	*
2007	I(n_fl_std^2)	-0.0154757	0.0749122	-0.2065841	0.8368119	
2007	FFD_std:n_fl_std	0.3941541	0.2660763	1.4813576	0.1420832	
2008	(Intercept)	0.9849204	0.1282534	7.6794886	0.0000000	*
2008	FFD_std	-0.3237571	0.1570495	-2.0614965	0.0427215	*
2008	I(FFD_std^2)	0.0727882	0.0665904	1.0930730	0.2778603	
2008	n_fl_std	0.8313144	0.2113209	3.9338963	0.0001850	*
2008	I(n_fl_std^2)	-0.1007195	0.0827089	-1.2177595	0.2271328	
2008	FFD_std:n_fl_std	-0.0964812	0.2458104	-0.3925027	0.6958001	
2009	(Intercept)	1.8943698	0.4033058	4.6971054	0.0000180	*
2009	FFD_std	0.9186105	0.4482712	2.0492292	0.0452217	*
2009	I(FFD_std^2)	-0.0626484	0.3025368	-0.2070770	0.8367145	
2009	n_fl_std	2.3412986	0.7607277	3.0777089	0.0032499	*
2009	I(n_fl_std^2)	-0.1456065	0.1675936	-0.8688067	0.3887284	
2009	FFD_std:n_fl_std	1.2853730	0.7940478	1.6187603	0.1112198	
2010	(Intercept)	1.1476515	0.2627212	4.3683250	0.0000438	*
2010	FFD_std	-0.3044103	0.2611880	-1.1654833	0.2478954	
2010	I(FFD_std^2)	0.1956397	0.1653152	1.1834344	0.2407578	
2010	n_fl_std	0.6117473	0.3834876	1.5952206	0.1153005	
2010	I(n_fl_std^2)	-0.1433445	0.1391728	-1.0299752	0.3066713	
2010	FFD_std:n_fl_std	0.3794815	0.3577730	1.0606768	0.2925897	
2011	(Intercept)	0.7410165	0.2639969	2.8069142	0.0062803	*
2011	FFD_std	-0.5840558	0.3081004	-1.8956670	0.0616154	
2011	I(FFD_std^2)	0.0517437	0.1712146	0.3022153	0.7632723	
2011	n_fl_std	0.4252056	0.3801078	1.1186447	0.2666395	
2011	I(n_fl_std^2)	0.0401968	0.1775753	0.2263648	0.8214951	
2011	FFD_std:n_fl_std	-0.3183722	0.5065314	-0.6285340	0.5314446	
2012	(Intercept)	0.5559600	0.2510678	2.2143819	0.0289849	*
2012	FFD_std	-1.0250419	0.2500524	-4.0993085	0.0000824	*
2012	I(FFD_std^2)	0.3702394	0.1873675	1.9760065	0.0508028	
2012	n_fl_std	0.5262771	0.3918890	1.3429240	0.1822201	
2012	I(n_fl_std^2)	-0.0973823	0.1459070	-0.6674274	0.5059775	
2012	FFD_std:n_fl_std	-0.3349938	0.4303492	-0.7784232	0.4380870	
2013	(Intercept)	1.0003734	0.5371658	1.8623177	0.0672230	
2013	FFD_std	-0.2769202	0.3797226	-0.7292695	0.4685395	
2013	I(FFD_std^2)	0.1780980	0.3624769	0.4913361	0.6248962	
2013	n_fl_std	0.1691522	0.5019523	0.3369886	0.7372455	
2013	I(n_fl_std^2)	-0.0881300	0.3374596	-0.2611572	0.7948231	
2013	FFD_std:n_fl_std	0.4550790	0.4491692	1.0131571	0.3148605	
2014	(Intercept)	0.8661868	0.2458628	3.5230496	0.0008481	*
2014	FFD_std	-0.6135471	0.2287960	-2.6816344	0.0095667	*
2014	I(FFD_std^2)	0.3400106	0.2066816	1.6450935	0.1054548	
2014	n_fl_std	0.0988467	0.3604495	0.2742319	0.7848978	
2014	I(n_fl_std^2)	-0.0243670	0.1429300	-0.1704823	0.8652345	
2014	FFD_std:n_fl_std	0.3147446	0.3514151	0.8956490	0.3742072	

year	term	estimate	std.error	statistic	p.value	sig
2015	(Intercept)	1.9568387	0.3657597	5.3500661	0.0000087	*
2015	FFD_std	0.2859020	0.2905912	0.9838631	0.3330516	
2015	I(FFD_std^2)	-0.9753178	0.3640841	-2.6788255	0.0118735	*
2015	n_fl_std	0.8696845	0.4117254	2.1122926	0.0430951	*
2015	I(n_fl_std^2)	-0.7020960	0.3098146	-2.2661815	0.0308156	*
2015	FFD_std:n_fl_std	-1.0408931	0.5552089	-1.8747773	0.0705891	
2016	(Intercept)	1.1990917	0.1262100	9.5007650	0.0000000	*
2016	FFD_std	0.2192984	0.1418922	1.5455281	0.1252273	
2016	I(FFD_std^2)	0.0047030	0.0762311	0.0616939	0.9509239	
2016	n_fl_std	0.8340557	0.1759506	4.7402849	0.0000067	*
2016	I(n_fl_std^2)	0.0509106	0.0851579	0.5978376	0.5512356	
2016	FFD_std:n_fl_std	0.5000387	0.1893912	2.6402432	0.0095479	*
2017	(Intercept)	0.9089216	0.6704120	1.3557656	0.1776578	
2017	FFD_std	-0.1913364	0.6331865	-0.3021802	0.7630250	
2017	I(FFD_std^2)	-0.2056510	0.4058771	-0.5066830	0.6132843	
2017	n_fl_std	-1.0750392	0.9749933	-1.1026119	0.2723485	
2017	I(n_fl_std^2)	0.2941794	0.5491987	0.5356521	0.5931663	
2017	FFD_std:n_fl_std	-0.0059586	0.7585858	-0.0078548	0.9937455	

```
#Correlational selection in 1988, 2016
#Quadratic selection on n_fl in 1990, 2006, 2015 and on FFD in 2015
kable(sel_models3_rsq) #R squares
```

year	r.squared	adj.r.squared
1987	0.2818452	0.2663678
1988	0.2029259	0.1787721
1989	0.3805970	0.3469338
1990	0.2054147	0.1741318
1991	0.3972959	0.3799768
1992	0.0808863	0.0391084
1993	0.0873721	0.0606870
1994	0.0474307	0.0211166
1995	0.1079986	-0.0158905
1996	0.2942184	0.2643124
2006	0.4206109	0.3876910
2007	0.1910072	0.1450417
2008	0.4731036	0.4379771
2009	0.1686804	0.0931058
2010	0.1711221	0.1101752
2011	0.2639200	0.2179150
2012	0.3678178	0.3374244
2013	0.0424174	-0.0335812
2014	0.2672590	0.2029835
2015	0.2637203	0.1410070
2016	0.3947962	0.3659769
2017	0.0151461	-0.0248886

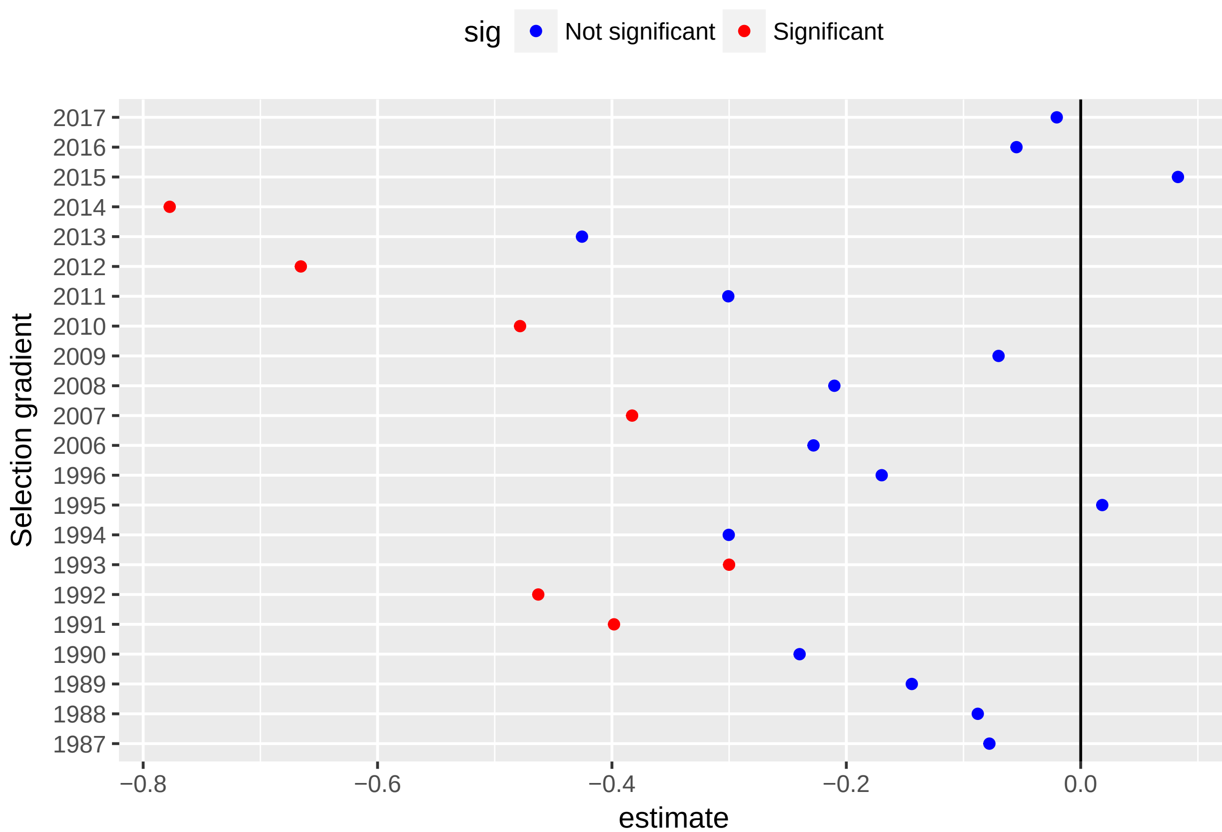
```
kable(sel_models3_anova) #Anova results
```

year	variable	F.value	Pr..F.	sig
1987	FFD_std	0.0157473	0.9002457	
1987	I(FFD_std^2)	0.6987816	0.4040535	
1987	n_fl_std	27.7831715	0.0000003	*
1987	I(n_fl_std^2)	0.0116974	0.9139665	
1987	FFD_std:n_fl_std	0.0033622	0.9538112	
1988	FFD_std	0.3162742	0.5746186	
1988	I(FFD_std^2)	1.4593577	0.2287610	
1988	n_fl_std	6.6965130	0.0105215	*
1988	I(n_fl_std^2)	1.8284980	0.1781555	
1988	FFD_std:n_fl_std	10.4715629	0.0014650	*
1989	FFD_std	1.4636489	0.2294499	
1989	I(FFD_std^2)	0.0672715	0.7959311	
1989	n_fl_std	7.9730824	0.0058201	*
1989	I(n_fl_std^2)	0.4475679	0.5051675	
1989	FFD_std:n_fl_std	0.0734244	0.7870217	
1990	FFD_std	0.5337332	0.4663872	
1990	I(FFD_std^2)	0.1683052	0.6823137	
1990	n_fl_std	20.8786629	0.0000114	*
1990	I(n_fl_std^2)	10.1473489	0.0018185	*
1990	FFD_std:n_fl_std	1.5974395	0.2085814	
1991	FFD_std	20.8547707	0.0000093	*
1991	I(FFD_std^2)	0.2025037	0.6532676	
1991	n_fl_std	7.7854453	0.0058546	*
1991	I(n_fl_std^2)	1.9844549	0.1607063	
1991	FFD_std:n_fl_std	0.5511514	0.4588486	
1992	FFD_std	2.7919117	0.0975840	
1992	I(FFD_std^2)	0.2758624	0.6004831	
1992	n_fl_std	1.5849424	0.2107154	
1992	I(n_fl_std^2)	3.2535026	0.0740080	
1992	FFD_std:n_fl_std	0.4633946	0.4974722	
1993	FFD_std	3.1242200	0.0789203	
1993	I(FFD_std^2)	0.0297740	0.8632081	
1993	n_fl_std	3.3510498	0.0689029	
1993	I(n_fl_std^2)	0.2954244	0.5874731	
1993	FFD_std:n_fl_std	0.6191688	0.4324455	
1994	FFD_std	1.1833370	0.2781241	
1994	I(FFD_std^2)	0.0108048	0.9173270	
1994	n_fl_std	2.5257070	0.1137498	
1994	I(n_fl_std^2)	0.3330138	0.5646069	
1994	FFD_std:n_fl_std	0.1185826	0.7309767	
1995	FFD_std	0.5160813	0.4771550	
1995	I(FFD_std^2)	0.5523012	0.4622016	
1995	n_fl_std	3.1645544	0.0836985	
1995	I(n_fl_std^2)	1.6455822	0.2077592	
1995	FFD_std:n_fl_std	0.1205607	0.7304489	
1996	FFD_std	2.3982139	0.1241518	
1996	I(FFD_std^2)	0.2793402	0.5981267	
1996	n_fl_std	14.3506043	0.0002403	*
1996	I(n_fl_std^2)	0.4410397	0.5079167	
1996	FFD_std:n_fl_std	0.0016866	0.9673107	
2006	FFD_std	0.7568442	0.3866848	
2006	I(FFD_std^2)	2.3014362	0.1328387	

year	variable	F.value	Pr..F.	sig
2006	n_fl_std	44.6062382	0.0000000	*
2006	I(n_fl_std^2)	6.9780732	0.0097642	*
2006	FFD_std:n_fl_std	2.9327608	0.0903206	
2007	FFD_std	4.7517566	0.0319384	*
2007	I(FFD_std^2)	2.6437239	0.1075357	
2007	n_fl_std	2.4134752	0.1238843	
2007	I(n_fl_std^2)	0.0426770	0.8368119	
2007	FFD_std:n_fl_std	2.1944204	0.1420832	
2008	FFD_std	4.2453792	0.0428259	*
2008	I(FFD_std^2)	1.1948085	0.2778603	
2008	n_fl_std	17.2590684	0.0000855	*
2008	I(n_fl_std^2)	1.4829382	0.2271328	
2008	FFD_std:n_fl_std	0.1540583	0.6958001	
2009	FFD_std	2.1230700	0.1507814	
2009	I(FFD_std^2)	0.0428809	0.8367145	
2009	n_fl_std	6.9539905	0.0108509	*
2009	I(n_fl_std^2)	0.7548251	0.3887284	
2009	FFD_std:n_fl_std	2.6203850	0.1112198	
2010	FFD_std	2.3826577	0.1273300	
2010	I(FFD_std^2)	1.4005170	0.2407578	
2010	n_fl_std	1.8836772	0.1744269	
2010	I(n_fl_std^2)	1.0608488	0.3066713	
2010	FFD_std:n_fl_std	1.1250352	0.2925897	
2011	FFD_std	3.3775309	0.0698034	
2011	I(FFD_std^2)	0.0913341	0.7632723	
2011	n_fl_std	2.2198295	0.1401803	
2011	I(n_fl_std^2)	0.0512410	0.8214951	
2011	FFD_std:n_fl_std	0.3950550	0.5314446	
2012	FFD_std	16.1991554	0.0001084	*
2012	I(FFD_std^2)	3.9046017	0.0508028	
2012	n_fl_std	2.4630875	0.1195871	
2012	I(n_fl_std^2)	0.4454593	0.5059775	
2012	FFD_std:n_fl_std	0.6059427	0.4380870	
2013	FFD_std	1.3164480	0.2555691	
2013	I(FFD_std^2)	0.2414111	0.6248962	
2013	n_fl_std	0.0487339	0.8259952	
2013	I(n_fl_std^2)	0.0682031	0.7948231	
2013	FFD_std:n_fl_std	1.0264873	0.3148605	
2014	FFD_std	6.9098271	0.0109980	*
2014	I(FFD_std^2)	2.7063326	0.1054548	
2014	n_fl_std	0.1504880	0.6995144	
2014	I(n_fl_std^2)	0.0290642	0.8652345	
2014	FFD_std:n_fl_std	0.8021871	0.3742072	
2015	FFD_std	0.6941762	0.4113320	
2015	I(FFD_std^2)	7.1761062	0.0118735	*
2015	n_fl_std	3.5442102	0.0694841	
2015	I(n_fl_std^2)	5.1355784	0.0308156	*
2015	FFD_std:n_fl_std	3.5147899	0.0705891	
2016	FFD_std	1.4430650	0.2323467	
2016	I(FFD_std^2)	0.0038061	0.9509239	
2016	n_fl_std	20.1304560	0.0000186	*
2016	I(n_fl_std^2)	0.3574098	0.5512356	

year	variable	F.value	Pr..F.	sig
2016	FFD_std:n_fl_std	6.9708839	0.0095479	*
2017	FFD_std	0.0913191	0.7630172	
2017	I(FFD_std^2)	0.2567277	0.6132843	
2017	n_fl_std	1.2812416	0.2598702	
2017	I(n_fl_std^2)	0.2869232	0.5931663	
2017	FFD_std:n_fl_std	0.0000617	0.9937455	

Selection gradients for FFD for each year, from models including also number of flowers



Models to explain variation in selection gradients among years

How are yearly selection gradients linked to climatic variables?

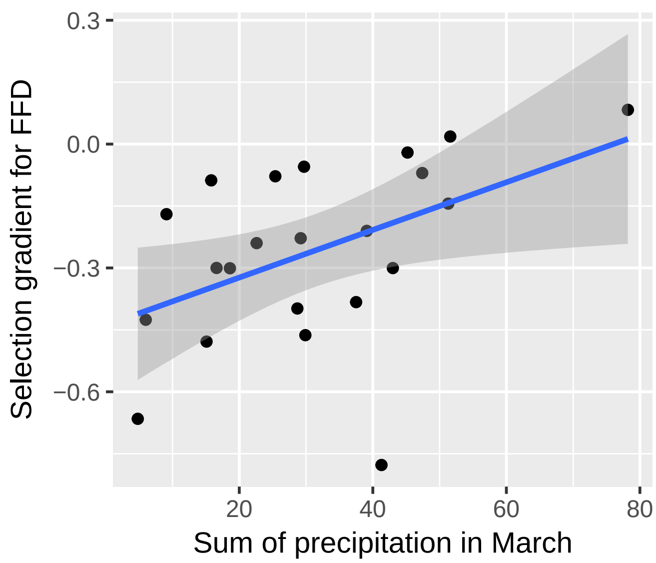
```
sel_grads_FFD$signif<-as.factor(with(sel_grads_FFD,ifelse(sig=="*","1","0")))
sel_grads_FFD$sig<-NULL
names(sel_grads_FFD)<-c("year","selgradFFD","sig_selgradFFD")
data_sel_agg<-merge(mean_weather5,sel_grads_FFD)

#Fit univariate linear models of selgradFFD against each predictor (climatic variables)
varlist<-names(data_sel_agg)[c(8:10,20:22,32:34,42:46,56:58,68:70,80:82,
                  92:94,104:106,116:118,128:130,134,138:142,146:217,217,223:232)]
```

```r
models_selgrads<-lapply(varlist, function(x) {
  summary(lm(substitute(selgradFFD ~ scale(i), list(i = as.name(x))),data=data_sel_agg))})

#Build a table with estimate, p and r square for all fitted models
models_selgrads<-cbind(varlist,
              plyr::ldply(models_selgrads, function(x) coef(x)[2]),
              plyr::ldply(models_selgrads, function(x) coef(x)[8]),
              plyr::ldply(models_selgrads, function(x) x$adj.r.square))
names(models_selgrads)<-c("variable","estimate","p","adj.rsquare")
models_selgrads$sig<-ifelse(models_selgrads$p<0.05,"*","") # *=p<0.05

#Order models with significant variables by R square
kable(arrange(subset(models_selgrads,sig=="*"),desc(adj.rsquare)))
```

variable	estimate	p	adj.rsquare	sig
precipitation_3	0.1026412	0.0277206	0.1808409	*

Only precipitation in March is significant.

Plot of the best model



The model without interaction explains 18% of variance in selection gradients for FFD. Selection for early flowering (i.e. a more negative selection gradient) is stronger with lower precipitation in March. This means that when March is dry, there is more advantage of flowering early. Why?? The effect of precipitation in March might be related to the amount of snow and vegetative development? If March is dry (i.e. there is not a lot of snow), it is an advantage to start vegetative development earlier (which also would mean flowering earlier).

How are yearly selection gradients linked to mean of FFD?

```r
kable(prettify(summary(lm(selgradFFD~FFD_mean,data=data_sel_agg)))) #No effect of FFD_mean
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.6161654	-1.612337	0.3800060	0.4775594	-1.2902383	0.212
FFD_mean	0.0061609	-0.010928	0.0232497	0.0081923	0.7520298	0.461

How are yearly selection gradients linked to variance of FFD?

```
kable(prettify(summary(lm(selgradFFD~FFD_var,data=data_sel_agg)))) #No effect of FFD_var
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.2789569	-0.5082876	-0.0496261	0.1099400	-2.5373563	0.02	*
FFD_var	0.0008638	-0.0079792	0.0097067	0.0042393	0.2037501	0.841	

How are yearly selection gradients linked to range of FFD?

```
kable(prettify(summary(lm(selgradFFD~FFD_dur,data=data_sel_agg)))) #No effect of FFD_dur
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.4203573	-0.8031190	-0.0375956	0.1834939	-2.2908509	0.033	*
FFD_dur	0.0072841	-0.0093993	0.0239676	0.0079980	0.9107492	0.373	

How are yearly selection gradients linked to skewness of FFD?

```
kable(prettify(summary(lm(selgradFFD~FFD_skew,data=data_sel_agg)))) #No effect of FFD_skew
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.2757119	-0.3986803	-0.1527436	0.0589504	-4.677018	<0.001	***
FFD_skew	0.0431151	-0.1420324	0.2282626	0.0887588	0.485756	0.632	

How are yearly selection gradients linked to kurtosis of FFD?

```
kable(prettify(summary(lm(selgradFFD~FFD_kurt,data=data_sel_agg)))) #No effect of FFD_kurt
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.3609793	-0.6284916	-0.0934671	0.1282440	-2.8147858	0.011	*
FFD_kurt	0.0311420	-0.0447111	0.1069951	0.0363636	0.8564056	0.402	

How are yearly selection gradients linked to intensity of grazing?

```
data_sel_agg<-merge(data_sel_agg,aggregate(grazing~year,data_sel,FUN=mean))

#Added mean grazing per year
```

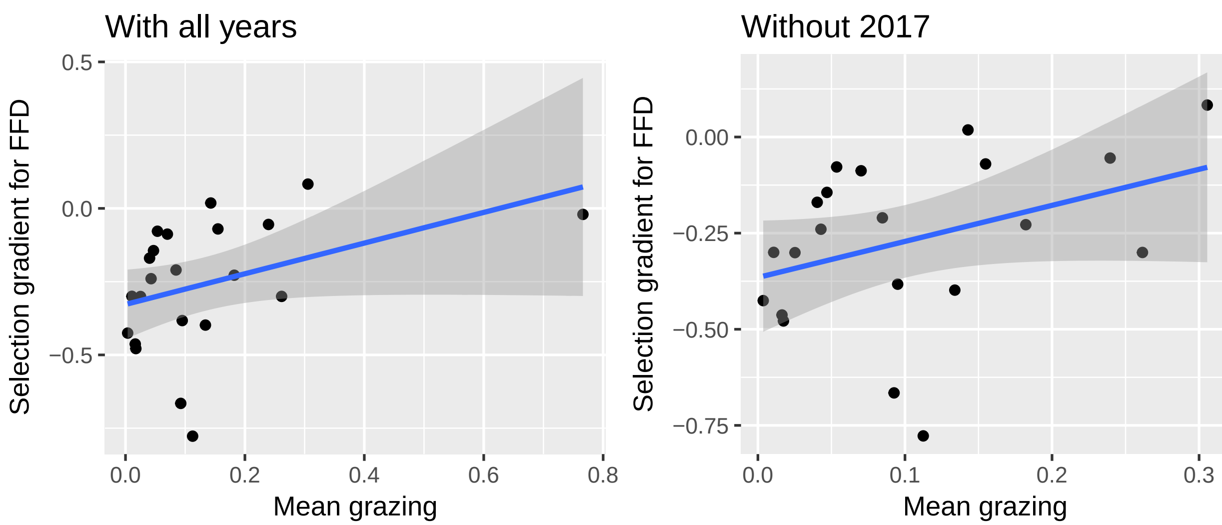
```r
kable(prettify(summary(lm(selgradFFD~grazing,data=data_sel_agg))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.3277413	-0.4461103	-0.2093722	0.0567455	-5.775635	<0.001	***
grazing	0.5234351	-0.0450517	1.0919219	0.2725296	1.920654	0.069	.

```r
      #p=0.0691
kable(prettify(summary(lm(selgradFFD~grazing,data=subset(data_sel_agg,year<2017)))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.3653455	-0.5130758	-0.2176152	0.0705822	-5.176169	<0.001	***
grazing	0.9377484	-0.1800222	2.0555190	0.5340458	1.755933	0.095	.

```r
      #Removing 2017, worse p=0.0948
#No effect of grazing (or very low effect?)
```



Although the effects are not significant, a higher grazing pressure seems to favor selection for later flowering.

How are yearly selection gradients linked to seed predation?

```r
data_sel$n_pred_seeds<-with(data_sel,n_seeds-n_intact_seeds)
data_sel$prop_pred_seeds<-with(data_sel,
        ifelse(n_seeds==n_intact_seeds,0,
               (data_sel$n_seeds-data_sel$n_intact_seeds)/data_sel$n_seeds))
data_sel_agg<-merge(data_sel_agg,aggregate(prop_pred_seeds~year,data_sel,FUN=mean))
data_sel_agg<-merge(data_sel_agg,aggregate(n_pred_seeds~year,data_sel,FUN=mean))
data_sel_agg<-merge(data_sel_agg,aggregate(n_seeds~year,data_sel,FUN=mean))

#Added mean seed predation (proportion and n of predated seeds) per year
kable(prettify(summary(lm(selgradFFD~prop_pred_seeds,data=data_sel_agg)))) #NS
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.1794939	-0.3314173	-0.0275706	0.0728313	-2.464517	0.023	*
prop_pred_seeds	-0.3973852	-0.9906960	0.1959256	0.2844301	-1.397128	0.178	

```
kable(prettify(summary(lm(selgradFFD~n_pred_seeds,data=data_sel_agg)))) #NS
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.2239353	-0.3658058	-0.0820648	0.0680120	-3.2925857	0.004	**
n_pred_seeds	-0.0118803	-0.0466844	0.0229238	0.0166849	-0.7120391	0.485	

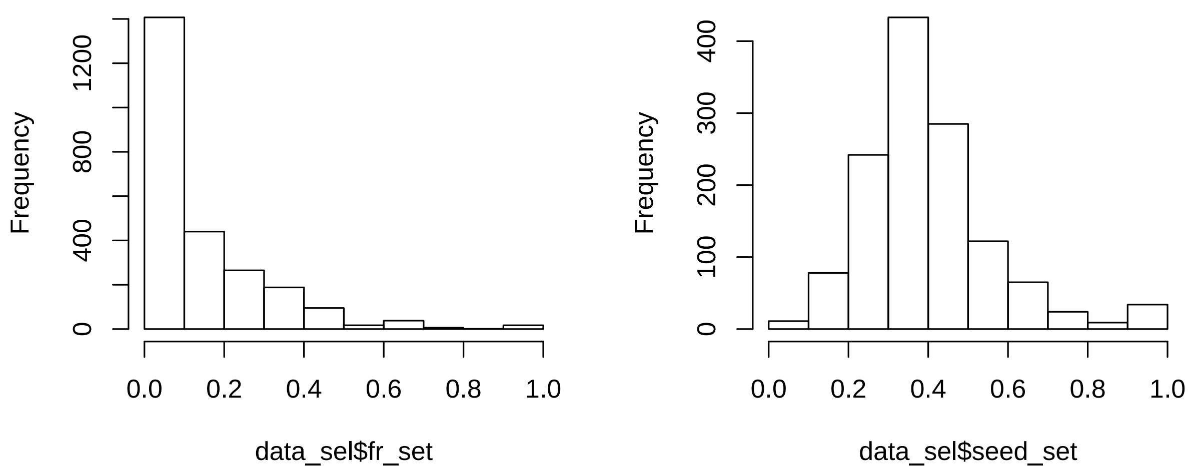
No effect of seed predation on selection gradients.

How are yearly selection gradients linked to fruit and seed set?

```
data_sel$fr_set<-with(data_sel,n_fr/n_fl)           #Calculate fruit set
data_sel$seed_set<-with(data_sel,n_seeds/n_ovules)  #Calculate seed set
nrow(subset(data_sel,n_fr>n_fl)) #0 cases where n_fruits>n_flowers
```

```
## [1] 0
```

```
par(mfrow=c(1,2))
hist(data_sel$fr_set,main=NULL)
hist(data_sel$seed_set,main=NULL)
```




```
data_sel_agg<-merge(data_sel_agg,aggregate(fr_set~year,data_sel,FUN=mean))
data_sel_agg<-merge(data_sel_agg,aggregate(seed_set~year,data_sel,FUN=mean))

kable(prettify(summary(lm(selgradFFD~fr_set,data=data_sel_agg)))) #NS
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.3691755	-0.5934844	-0.1448666	0.1075325	-3.433152	0.003	**
fr_set	0.8490418	-0.7076631	2.4057467	0.7462762	1.137704	0.269	

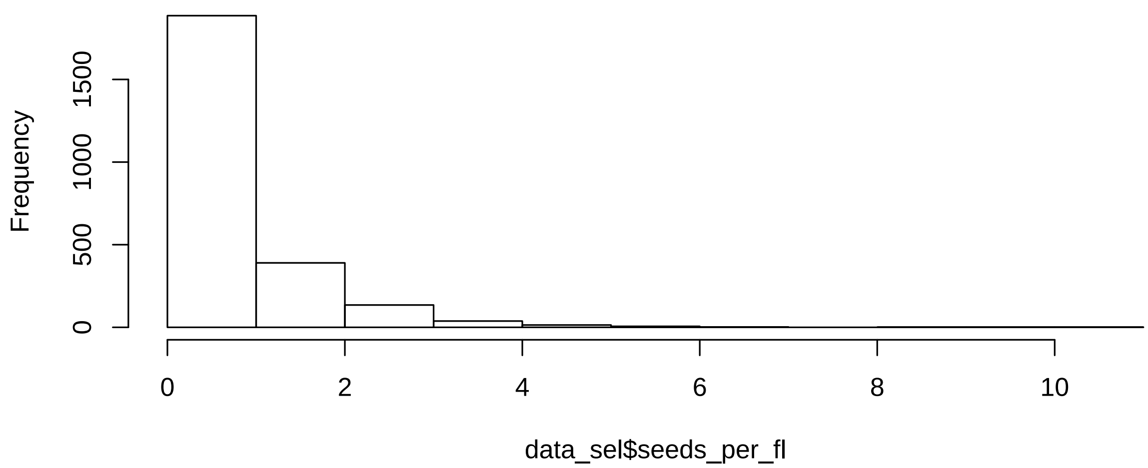
```
kable(prettify(summary(lm(selgradFFD~seed_set,data=data_sel_agg)))) #NS
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0746177	-0.5985151	0.4492796	0.2511537	-0.2970999	0.769
seed_set	-0.4438252	-1.6839181	0.7962678	0.5944941	-0.7465594	0.464

No effect of fruit and seed set on selection gradients.

How are yearly selection gradients linked to number of seeds per flower?

```
data_sel$seeds_per_fl<-with(data_sel,n_seeds/n_fl)  #Calculate n seeds per fl
hist(data_sel$seeds_per_fl,main=NULL)
```




```
data_sel_agg<-merge(data_sel_agg,aggregate(seeds_per_fl~year,data_sel,FUN=mean))

kable(prettify(summary(lm(selgradFFD~seeds_per_fl,data=data_sel_agg)))) #NS
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.3735444	-0.5793023	-0.1677865	0.0986393	-3.786974	0.001	**
seeds_per_fl	0.1728408	-0.1014791	0.4471607	0.1315075	1.314304	0.204	

No effect of number of seeds per flower on selection gradients.

How are yearly selection gradients linked to grazing, seed predation, fruit and seed set? (alltogether)

```
summary(lm(selgradFFD~grazing+prop_pred_seeds+fr_set+seed_set,data=data_sel_agg)) #Grazing*
```

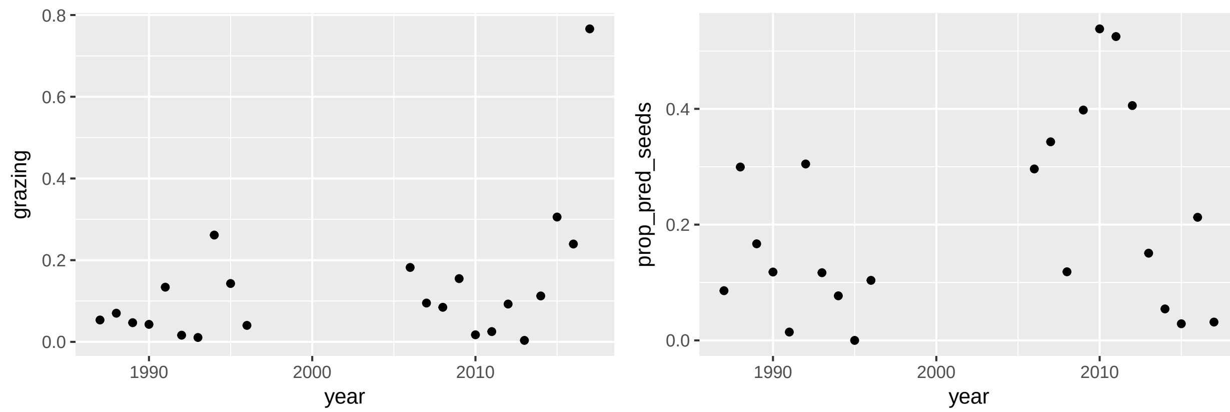
```
##
## Call:
## lm(formula = selgradFFD ~ grazing + prop_pred_seeds + fr_set +
##     seed_set, data = data_sel_agg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.50787 -0.08522  0.03295  0.10956  0.29271
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -0.10992    0.23929  -0.459   0.6518
## grazing          0.75162    0.30535   2.462   0.0248 *
## prop_pred_seeds -0.04362    0.28601  -0.153   0.8806
## fr_set           1.19108    0.68961   1.727   0.1023
## seed_set        -0.94963    0.56540  -1.680   0.1113
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1921 on 17 degrees of freedom
## Multiple R-squared:  0.3767, Adjusted R-squared:   0.23
## F-statistic: 2.568 on 4 and 17 DF,  p-value: 0.07562
```

```
summary(lm(selgradFFD~grazing+prop_pred_seeds+seeds_per_fl,data=data_sel_agg)) #NS
```

```
##
## Call:
## lm(formula = selgradFFD ~ grazing + prop_pred_seeds + seeds_per_fl,
##     data = data_sel_agg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.51442 -0.07647  0.01777  0.10105  0.29550
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.4242     0.1337  -3.173  0.00526 **
## grazing           0.5213     0.2874   1.814  0.08642 .
## prop_pred_seeds  -0.1670     0.2881  -0.580  0.56921
## seeds_per_fl      0.1959     0.1253   1.563  0.13536
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2003 on 18 degrees of freedom
## Multiple R-squared:  0.2825, Adjusted R-squared:  0.163
## F-statistic: 2.363 on 3 and 18 DF,  p-value: 0.1052
```

Grazing is significant: there is increased selection for late flowering in years of more intense grazing (as expected because grazers attack more the early-flowering ones).

Models to explain variation in grazing and seed predation among years



Grazing

How is grazing linked to climatic variables?

```
#Fit univariate linear models of grazing against each predictor (climatic variables)
models_grazing<-lapply(varlist, function(x) {
  summary(lm(substitute(log(grazing) ~ scale(i), list(i = as.name(x))),data=data_sel_agg))})

#Build a table with estimate, p and r square for all fitted models
models_grazing<-cbind(varlist,
              plyr::ldply(models_grazing, function(x) coef(x)[2]),
              plyr::ldply(models_grazing, function(x) coef(x)[8]),
              plyr::ldply(models_grazing, function(x) x$adj.r.squared)
              )

names(models_grazing)<-c("variable","estimate","p","rsquare")
models_grazing$sig<-ifelse(models_grazing$p<0.05,"*","") # *=p<0.05

#Order models with significant variables by R square
kable(arrange(subset(models_grazing,sig=="*"),desc(rsquare)))
```

variable	estimate	p	rsquare	sig
precipitation_3	0.7772630	0.0017654	0.3636389	*
GDD10_b	-0.6686661	0.0094892	0.2561287	*
min_5	-0.6368787	0.0143374	0.2277147	*
GDD10_45	-0.6210793	0.0174060	0.2141067	*
GDD10_5	-0.5924344	0.0243108	0.1903067	*
GDD7_5	-0.5599974	0.0346033	0.1647125	*
GDD3_5	-0.5525291	0.0373996	0.1590238	*
GDH10_45	-0.5496694	0.0385162	0.1568657	*
GDH3_5	-0.5477196	0.0392923	0.1554007	*
GDH7_5	-0.5477020	0.0392994	0.1553875	*
GDH10_5	-0.5457749	0.0400785	0.1539448	*
GDH5_5	-0.5444032	0.0406405	0.1529209	*

variable	estimate	p	rsquare	sig
GDD5_5	-0.5432110	0.0411339	0.1520331	*
GDD7_45	-0.5327222	0.0456790	0.1443063	*
GDH10_b	-0.5294533	0.0471723	0.1419291	*

It seems that grazing is higher when there is more precipitation in March and April-May are less warm.

Model with two of the best variables: precipitation in March and GDD10 April+May

```
summary(lm(log(grazing)~scale(precipitation_3)+scale(GDD10_45),data=data_sel_agg))
```

```
##
## Call:
## lm(formula = log(grazing) ~ scale(precipitation_3) + scale(GDD10_45),
##     data = data_sel_agg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.55042 -0.57845  0.04472  0.30857  2.13352
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -2.6427     0.1946 -13.582 3.11e-11 ***
## scale(precipitation_3)   0.6544     0.2075   3.153  0.00523 **
## scale(GDD10_45)         -0.4371     0.2075  -2.106  0.04871 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9126 on 19 degrees of freedom
## Multiple R-squared:  0.5087, Adjusted R-squared:  0.4569
## F-statistic: 9.835 on 2 and 19 DF,  p-value: 0.00117
```

This model explains 46% of the variation in grazing.

How is grazing linked to mean of FFD?

```
kable(prettify(summary(lm(log(grazing) ~ FFD_mean,data=data_sel_agg))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.9410352	-7.646101	3.7640308	2.7349789	-0.7097076	0.486
FFD_mean	-0.0120953	-0.109963	0.0857724	0.0469173	-0.2578003	0.799

```
    #No effect of FFD_mean
kable(prettify(summary(lm(log(grazing) ~ FFD_mean,data=subset(data_sel_agg,!year=="2017")))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.8102440	-7.1073918	3.4869039	2.5308586	-0.7152687	0.483
FFD_mean	-0.0163171	-0.1072576	0.0746235	0.0434494	-0.3755423	0.711

```r
#Removing 2017, No effect of FFD_mean
```

How is grazing linked to variance of FFD?

```r
kable(prettify(summary(lm(log(grazing) ~ FFD_var,data=data_sel_agg))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3.8363940	-4.9784948	-2.6942931	0.5475172	-7.006893	<0.001	***
FFD_var	0.0511075	0.0070683	0.0951467	0.0211122	2.420761	0.025	*

```r
      #FFD_var*
summary(lm(log(grazing) ~ FFD_var,data=data_sel_agg))$adj.r.squared
```

```
## [1] 0.1879376
```

```r
kable(prettify(summary(lm(log(grazing) ~ FFD_var,data=subset(data_sel_agg,!year=="2017")))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-4.2739855	-5.2395708	-3.3084002	0.4613350	-9.264386	<0.001	***
FFD_var	0.0635902	0.0270198	0.1001607	0.0174725	3.639444	0.002	**

```r
#Removing 2017, FFD_var*
summary(lm(log(grazing) ~ FFD_var,data=subset(data_sel_agg,!year=="2017")))$adj.r.squared
```

```
## [1] 0.3797594
```

Grazing increases with variance of FFD.

How is grazing linked to range of FFD?

```r
kable(prettify(summary(lm(log(grazing) ~ FFD_dur,data=data_sel_agg)))) #FFD_dur*
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-4.758481	-6.7183564	-2.7986049	0.9395542	-5.064615	<0.001	***
FFD_dur	0.095385	0.0099599	0.1808102	0.0409524	2.329171	0.03	*

```r
summary(lm(log(grazing) ~ FFD_dur,data=data_sel_agg))$adj.r.squared
```

```
## [1] 0.1740425
```

```r
kable(prettify(summary(lm(log(grazing) ~ FFD_dur,data=subset(data_sel_agg,!year=="2017")))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-4.8858591	-6.6517063	-3.1200119	0.8436822	-5.791113	<0.001	***
FFD_dur	0.0959887	0.0191678	0.1728097	0.0367033	2.615260	0.017	*

```r
summary(lm(log(grazing) ~ FFD_dur,data=data_sel_agg))$adj.r.squared
```

```
## [1] 0.1740425
```

```r
#Removing 2017, FFD_dur*
```

Grazing increases with range of FFD.

How is grazing linked to skewness of FFD?

```r
kable(prettify(summary(lm(log(grazing) ~ FFD_skew,data=data_sel_agg))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.6301617	-3.329825	-1.930499	0.3354148	-7.8415208	<0.001	***
FFD_skew	-0.0318468	-1.085296	1.021602	0.5050180	-0.0630608	0.95	

```r
    #No effect of FFD_skew
kable(prettify(summary(lm(log(grazing) ~ FFD_skew,data=subset(data_sel_agg,!year=="2017")))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.8880170	-3.5780780	-2.197956	0.3296957	-8.759644	<0.001	***
FFD_skew	0.3075127	-0.7155909	1.330616	0.4888160	0.629097	0.537	

```r
#Removing 2017, No effect of FFD_skew
```

How is grazing linked to kurtosis of FFD?

```r
kable(prettify(summary(lm(log(grazing) ~ FFD_kurt,data=data_sel_agg))))
```

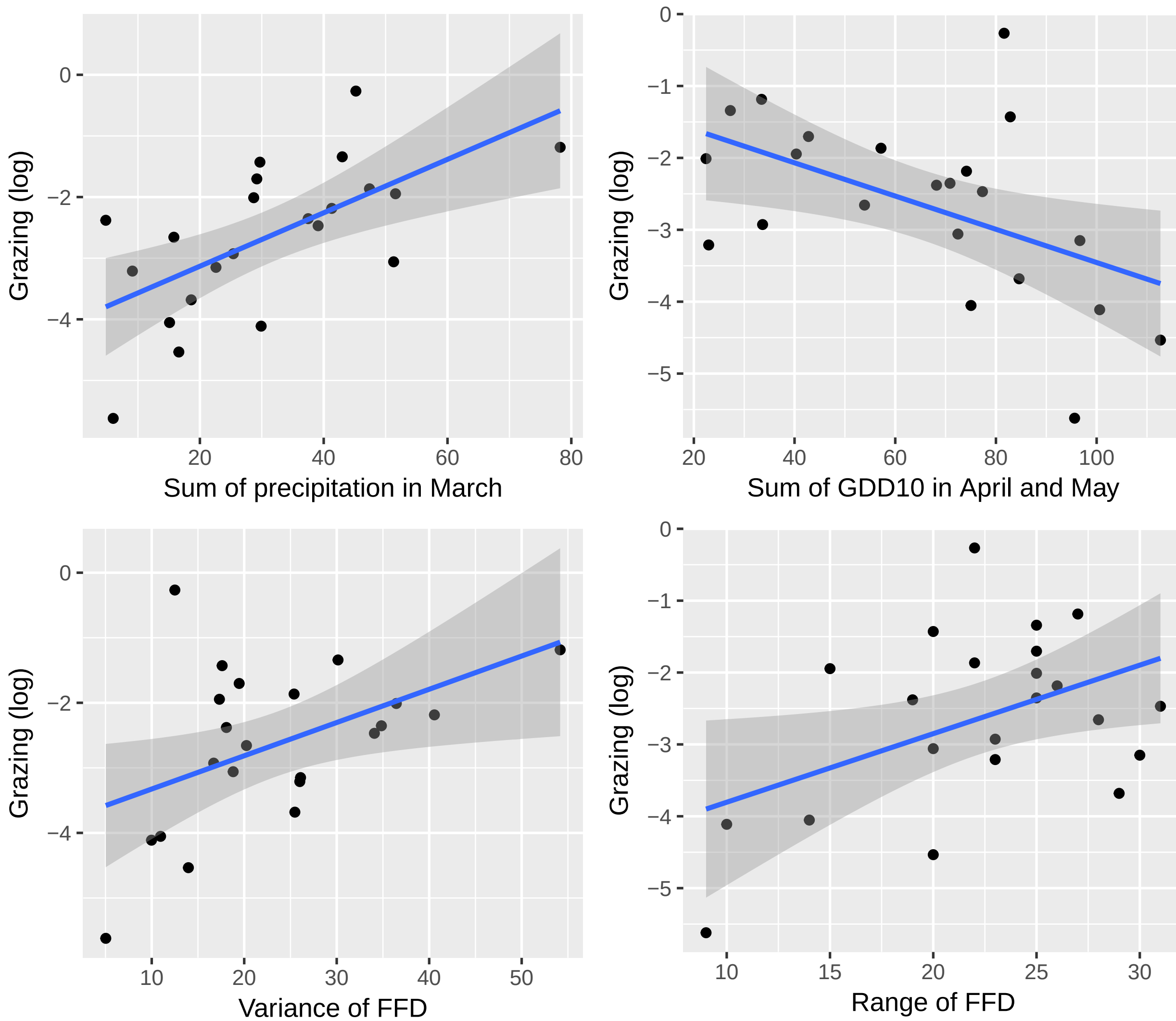
	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3.6299579	-5.0891530	-2.1707628	0.6995305	-5.189134	<0.001	***
FFD_kurt	0.3008514	-0.1129034	0.7146061	0.1983519	1.516756	0.145	

```r
    #No effect of FFD_kurt
kable(prettify(summary(lm(log(grazing) ~ FFD_kurt,data=subset(data_sel_agg,!year=="2017")))))
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	-3.3731171	-4.8073147	-1.9389194	0.6852275	-4.9226235	<0.001	***
FFD_kurt	0.1933492	-0.2247562	0.6114545	0.1997614	0.9679008	0.345	

```r
    #Removing 2017, No effect of FFD_kurt
```

Plots of best models grazing



Seed predation

How is seed predation linked to climatic variables?

```
#Fit univariate linear models of grazing against each predictor (climatic variables)
models_spred<-lapply(varlist, function(x) {
  summary(lm(substitute(asin(sqrt(prop_pred_seeds)) ~ scale(i),
             list(i = as.name(x))),data=data_sel_agg))})

#Build a table with estimate, p and r square for all fitted models
models_spred<-cbind(varlist,
              plyr::ldply(models_spred, function(x) coef(x)[2]),
              plyr::ldply(models_spred, function(x) coef(x)[8]),
              plyr::ldply(models_spred, function(x) x$adj.r.squared)
              )
```

```r
names(models_spred)<-c("variable","estimate","p","rsquare")
models_spred$sig<-ifelse(models_spred$p<0.05,"*","") # *=p<0.05

#Order models with significant variables by R square
kable(arrange(subset(models_spred,sig=="*"),desc(rsquare)))
```

variable	estimate	p	rsquare	sig
max456	0.1175066	0.0124084	0.2377486	*
GDH5_456	0.1133132	0.0165694	0.2175777	*
GDD3_456	0.1127731	0.0171790	0.2150328	*
GDH3_456	0.1126886	0.0172759	0.2146358	*
GDD5_456	0.1121752	0.0178747	0.2122299	*
GDH7_456	0.1121290	0.0179293	0.2120143	*
GDD7_456	0.1094296	0.0213676	0.1995507	*
mean456	0.1073061	0.0244286	0.1899592	*
GDD3_5	0.1072166	0.0245648	0.1895593	*
GDH3_5	0.1061410	0.0262510	0.1847766	*
GDH10_456	0.1057515	0.0268838	0.1830570	*
GDD5_5	0.1054809	0.0273307	0.1818655	*
GDD7_123456	0.1051687	0.0278533	0.1804953	*
GDH7_123456	0.1047364	0.0285902	0.1786044	*
max_5	0.1044491	0.0290885	0.1773518	*
GDH10_123456	0.1044371	0.0291096	0.1772995	*
min_5	0.1042951	0.0293586	0.1766817	*
GDH5_5	0.1038543	0.0301420	0.1747698	*
GDH7_45	0.1030942	0.0315321	0.1714915	*
precipitation_b	-0.1025554	0.0325477	0.1691824	*
precipitation_b	-0.1025554	0.0325477	0.1691824	*
precipitation_3	-0.1020538	0.0335162	0.1670438	*
GDH5_45	0.1017027	0.0342077	0.1655527	*
mean_5	0.1002929	0.0370974	0.1596185	*
GDD7_5	0.1000313	0.0376543	0.1585262	*
GDD7_45	0.0998181	0.0381128	0.1576384	*
GDD5_45	0.0995386	0.0387205	0.1564773	*
GDH7_5	0.0990908	0.0397102	0.1546234	*
GDD5_123456	0.0990350	0.0398348	0.1543932	*
GDD10_456	0.0982606	0.0415969	0.1512093	*
GDH3_45	0.0982002	0.0417368	0.1509620	*
GDD3_45	0.0980087	0.0421830	0.1501789	*
max45	0.0977048	0.0428987	0.1489393	*
GDD10_123456	0.0971879	0.0441377	0.1468399	*
max_6	0.0959804	0.0471404	0.1419792	*

It seems that seed predation increases with temperature/GDD/GDH from May to June.

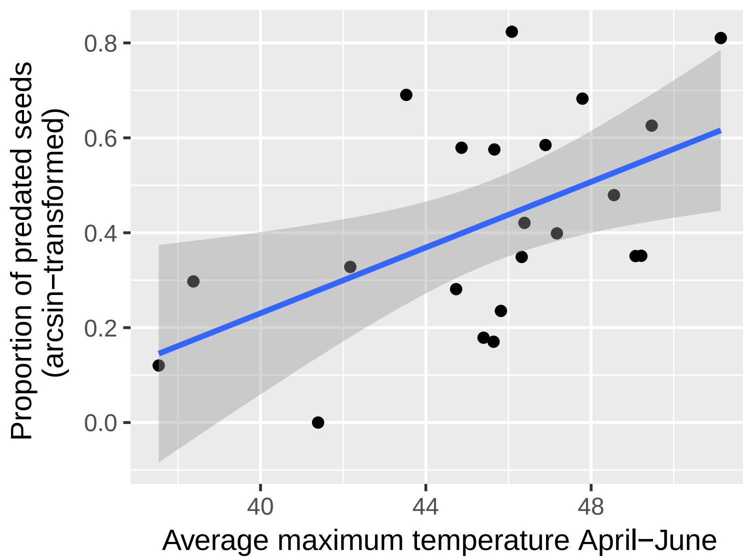
Model with one of the best variables:

```r
summary(lm(asin(sqrt(prop_pred_seeds))~scale(max456),data=data_sel_agg))
```

```
##
## Call:
## lm(formula = asin(sqrt(prop_pred_seeds)) ~ scale(max456), data = data_sel_agg)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.27863 -0.17353 -0.02782  0.14270  0.38268
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.42424    0.04178  10.154 2.45e-09 ***
## scale(max456)  0.11751    0.04277   2.748   0.0124 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.196 on 20 degrees of freedom
## Multiple R-squared:  0.274,  Adjusted R-squared:  0.2377
## F-statistic:  7.55 on 1 and 20 DF,  p-value: 0.01241
```

This model explains 24% of the variation in seed predation



How is seed predation linked to mean of FFD?

```
kable(prettify(summary(lm(sqrt(prop_pred_seeds) ~ FFD_mean,data=data_sel_agg)))) #No effect of FFD_mean
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.160843	0.3087713	2.0129140	0.4084786	2.841869	0.01	*
FFD_mean	-0.013088	-0.0277049	0.0015289	0.0070073	-1.867779	0.077	.

How is seed predation linked to variance of FFD?

```
kable(prettify(summary(lm(sqrt(prop_pred_seeds) ~ FFD_var,data=data_sel_agg)))) #No effect of FFD_var
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.5242616	0.3242516	0.7242716	0.0958837	5.467679	<0.001	***
FFD_var	-0.0052505	-0.0129629	0.0024618	0.0036973	-1.420107	0.171	

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)

How is seed predation linked to range of FFD?

```
kable(prettify(summary(lm(sqrt(prop_pred_seeds) ~ FFD_dur,data=data_sel_agg)))) #No effect of FFD_dur
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.4691719	0.1135924	0.8247513	0.1704629	2.752340	0.012	*
FFD_dur	-0.0030452	-0.0185438	0.0124535	0.0074300	-0.409849	0.686	

How is seed predation linked to skewness of FFD?

```
kable(prettify(summary(lm(sqrt(prop_pred_seeds) ~ FFD_skew,data=data_sel_agg)))) #No effect of FFD_skew
```

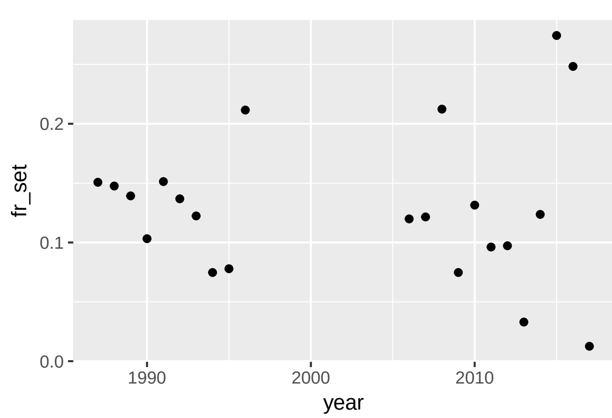
	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.3424016	0.2394387	0.4453645	0.0493599	6.936841	<0.001	***
FFD_skew	0.1508224	-0.0042039	0.3058487	0.0743188	2.029398	0.056	.

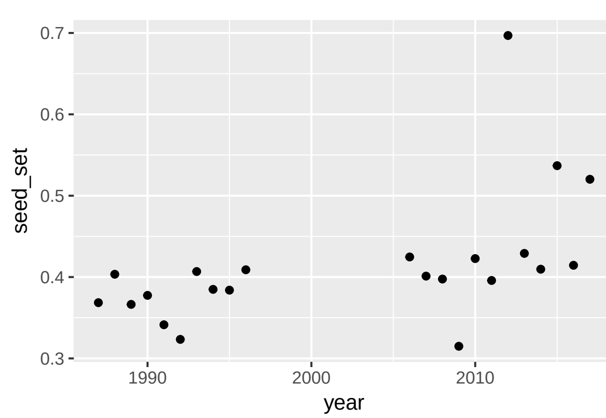
How is seed predation linked to kurtosis of FFD?

```
kable(prettify(summary(lm(sqrt(prop_pred_seeds) ~ FFD_kurt,data=data_sel_agg)))) #No effect of FFD_kurt
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.3243416	0.0783937	0.5702894	0.1179061	2.7508461	0.012	*
FFD_kurt	0.0235500	-0.0461885	0.0932885	0.0334323	0.7044092	0.489	

Models to explain variation in fruit and seed set among years





Fruit set

How is fruit set linked to climatic variables?

```
#Fit univariate linear models of fruit set against each predictor (climatic variables)
models_frset<-lapply(varlist, function(x) {
  summary(lm(substitute(fr_set ~ scale(i), list(i = as.name(x))),data=data_sel_agg))})

#Build a table with estimate, p and r square for all fitted models
models_frset<-cbind(varlist,
              plyr::ldply(models_frset, function(x) coef(x)[2]),
              plyr::ldply(models_frset, function(x) coef(x)[8]),
              plyr::ldply(models_frset, function(x) x$adj.r.squared)
              )

names(models_frset)<-c("variable","estimate","p","rsquare")
models_frset$sig<-ifelse(models_frset$p<0.05,"*","") # *=p<0.05

#Order models with significant variables by R square
kable(arrange(subset(models_frset,sig=="*"),desc(rsquare)))
```

variable estimate p rsquare sig ——— ——— — ——— —-

No significant relationships.

How is fruit set linked to mean of FFD?

```
kable(prettify(summary(lm(fr_set ~ FFD_mean,data=data_sel_agg)))) #No effect of FFD_mean FFD
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	0.2303611	-0.0591743	0.5198965	0.1388018	1.6596409	0.113
FFD_mean	-0.0017297	-0.0066966	0.0032371	0.0023811	-0.7264519	0.476

How is fruit set linked to variance of FFD?

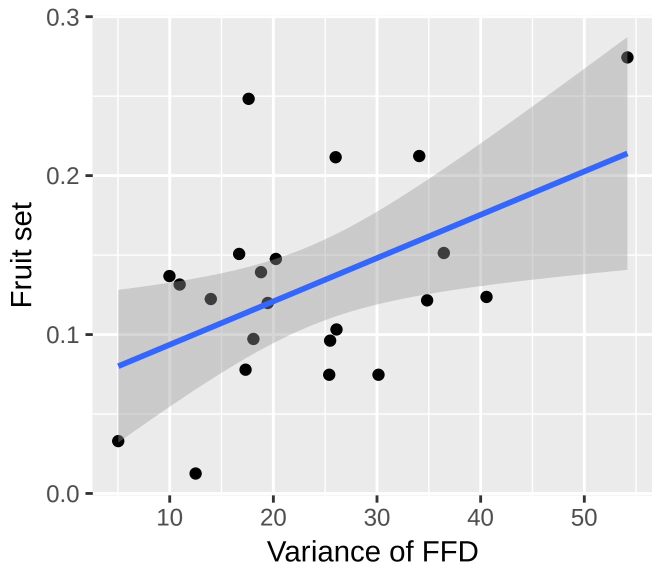
```
kable(prettify(summary(lm(fr_set ~ FFD_var,data=data_sel_agg)))) #FFD_var*
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.0663620	0.0084227	0.1243012	0.0277758	2.389204	0.027	*
FFD_var	0.0027255	0.0004913	0.0049596	0.0010710	2.544720	0.019	*

```
summary(lm(fr_set ~ FFD_var,data=data_sel_agg))$adj.r.square
```

```
## [1] 0.2068168
```

Fruit set increases with variance of FFD.



How is fruit set linked to range of FFD?

```
kable(prettify(summary(lm(fr_set ~ FFD_dur,data=data_sel_agg)))) #No effect of FFD_dur
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0587272	-0.0493605	0.1668148	0.0518166	1.133365	0.27
FFD_dur	0.0032141	-0.0014971	0.0079253	0.0022585	1.423081	0.17

How is fruit set linked to skewness of FFD?

```
kable(prettify(summary(lm(fr_set ~ FFD_skew,data=data_sel_agg)))) #No effect of FFD_skew
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.1232393	0.0877224	0.1587563	0.0170266	7.2380357	<0.001	***
FFD_skew	0.0172712	-0.0362049	0.0707474	0.0256362	0.6737058	0.508	

How is fruit set linked to kurtosis of FFD?

```
kable(prettify(summary(lm(fr_set ~ FFD_kurt,data=data_sel_agg)))) #No effect of FFD_kurt
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.1242423	0.0452034	0.2032812	0.0378908	3.2789545	0.004	**
FFD_kurt	0.0017610	-0.0206505	0.0241724	0.0107439	0.1639029	0.871	

Seed set

How is seed set linked to climatic variables?

```
#Fit univariate linear models of fruit set against each predictor (climatic variables)
models_seedset<-lapply(varlist, function(x) {
  summary(lm(substitute(seed_set ~ scale(i), list(i = as.name(x))),data=data_sel_agg))})

#Build a table with estimate, p and r square for all fitted models
models_seedset<-cbind(varlist,
              plyr::ldply(models_seedset, function(x) coef(x)[2]),
              plyr::ldply(models_seedset, function(x) coef(x)[8]),
              plyr::ldply(models_seedset, function(x) x$adj.r.squared)
              )

names(models_seedset)<-c("variable","estimate","p","rsquare")
models_seedset$sig<-ifelse(models_seedset$p<0.05,"*","") # *=p<0.05

#Order models with significant variables by R square
kable(arrange(subset(models_seedset,sig=="*"),desc(rsquare)))
```

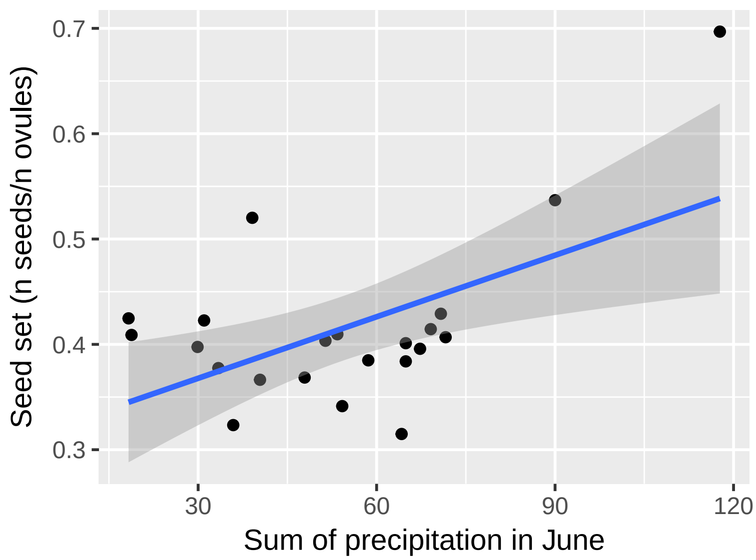
variable	estimate	p	rsquare	sig
precipitation_6	0.0456272	0.0065074	0.2814205	*
prec456	0.0417718	0.0143244	0.2277780	*
GDD7_3	0.0360799	0.0383232	0.1572343	*

Model with one of the best variables: precipitation in June

```
summary(lm(seed_set~scale(precipitation_6),data=data_sel_agg))
```

```
##
## Call:
## lm(formula = seed_set ~ scale(precipitation_6), data = data_sel_agg)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.11947 -0.04115 -0.01990  0.04670  0.15838
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.41495    0.01468  28.271  < 2e-16 ***
## scale(precipitation_6)  0.04563    0.01502   3.037  0.00651 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06884 on 20 degrees of freedom
## Multiple R-squared:  0.3156, Adjusted R-squared:  0.2814
## F-statistic: 9.224 on 1 and 20 DF,  p-value: 0.006507
```

This model explains 28% of the variation in seed set



How is seed set linked to mean of FFD

```
kable(prettify(summary(lm(seed_set ~ FFD_mean,data=data_sel_agg)))) #No effect of FFD_mean
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.5571557	0.1883670	0.9259444	0.1767954	3.1514156	0.005	**
FFD_mean	-0.0024515	-0.0087779	0.0038749	0.0030328	-0.8083145	0.428	

How is seed set linked to variance of FFD

```
kable(prettify(summary(lm(seed_set ~ FFD_var,data=data_sel_agg)))) #No effect of FFD_var
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.4080587	0.3229645	0.4931529	0.0407937	10.0029779	<0.001	***
FFD_var	0.0002950	-0.0029863	0.0035762	0.0015730	0.1875116	0.853	

How is seed set linked to range of FFD

```
kable(prettify(summary(lm(seed_set ~ FFD_dur,data=data_sel_agg)))) #No effect of FFD_dur
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.4181046	0.2731949	0.5630142	0.0694689	6.0185826	<0.001	***
FFD_dur	-0.0001423	-0.0064585	0.0061739	0.0030279	-0.0469972	0.963	

How is seed set linked to skewness of FFD

```
kable(prettify(summary(lm(seed_set ~ FFD_skew,data=data_sel_agg)))) #No effect of FFD_skew
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.4212267	0.3756058	0.4668476	0.0218704	19.2601077	<0.001	***
FFD_skew	-0.0159900	-0.0846792	0.0526992	0.0329293	-0.4855866	0.633	

How is seed set linked to kurtosis of FFD

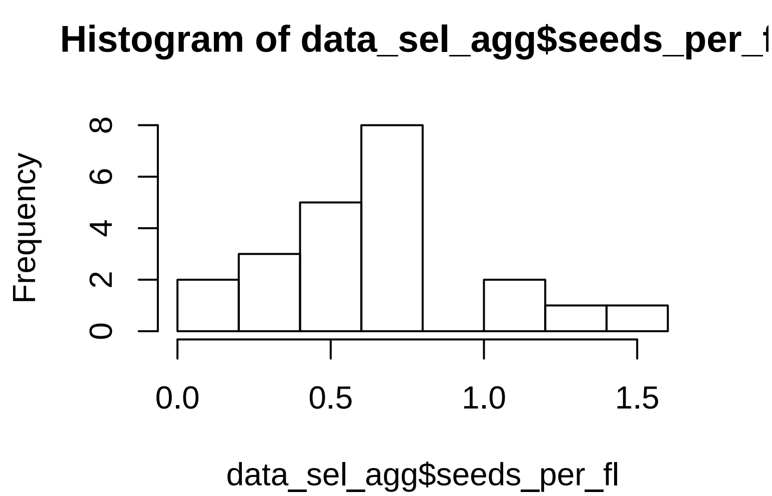
```
kable(prettify(summary(lm(seed_set ~ FFD_kurt,data=data_sel_agg)))) #No effect of FFD_kurt
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.3971794	0.2965234	0.4978354	0.0482539	8.2310250	<0.001	***
FFD_kurt	0.0054145	-0.0231265	0.0339555	0.0136824	0.3957283	0.696	

Models to explain variation in number of seeds per flower among years

How is number of seeds per flower linked to climatic variables?

```
hist(data_sel_agg$seeds_per_fl)
```




```
#Fit univariate linear models of fruit set against each predictor (climatic variables)
models_seeds_per_fl<-lapply(varlist, function(x) {
  summary(lm(substitute(seeds_per_fl ~ scale(i), list(i = as.name(x))),data=data_sel_agg))})

#Build a table with estimate, p and r square for all fitted models
models_seeds_per_fl<-cbind(varlist,
```

```r
             plyr::ldply(models_seeds_per_fl, function(x) coef(x)[2]),
             plyr::ldply(models_seeds_per_fl, function(x) coef(x)[8]),
             plyr::ldply(models_seeds_per_fl, function(x) x$adj.r.squared)
             )

names(models_seeds_per_fl)<-c("variable","estimate","p","rsquare")
models_seeds_per_fl$sig<-ifelse(models_seeds_per_fl$p<0.05,"*","") # *=p<0.05

#Order models with significant variables by R square
kable(arrange(subset(models_seeds_per_fl,sig=="*"),desc(rsquare)))
```

variable estimate p rsquare sig ——— ——— — ——— —-

No significant relationships.

How is number of seeds per flower linked to mean of FFD

```r
kable(prettify(summary(lm(seeds_per_fl ~ FFD_mean,data=data_sel_agg)))) #No effect of FFD_mean
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.405677	-0.2051486	3.0165032	0.7722215	1.8203031	0.084	.
FFD_mean	-0.012786	-0.0404190	0.0148469	0.0132471	-0.9651941	0.346	

How is number of seeds per flower linked to variance of FFD

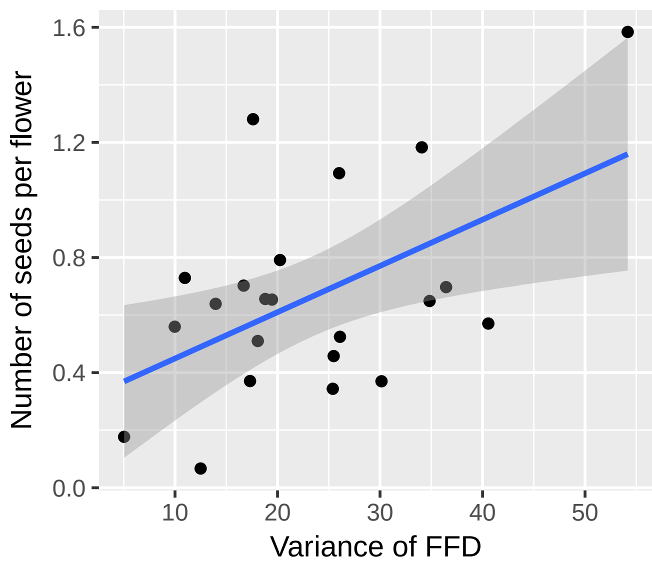
```r
kable(prettify(summary(lm(seeds_per_fl ~ FFD_var,data=data_sel_agg)))) #FFD_var*
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.2884017	-0.0316322	0.6084356	0.1534226	1.879787	0.075	.
FFD_var	0.0160797	0.0037392	0.0284201	0.0059159	2.718018	0.013	*

```r
summary(lm(seeds_per_fl ~ FFD_var,data=data_sel_agg))$adj.r.square
```

```
## [1] 0.2332303
```

Number of seeds per flower increases with FFD_var (as did fruit set).



How is number of seeds per flower linked to range of FFD

```r
kable(prettify(summary(lm(seeds_per_fl ~ FFD_dur,data=data_sel_agg)))) #No effect of FFD_dur
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)
(Intercept)	0.2199148	-0.3802276	0.8200571	0.2877051	0.7643756	0.454
FFD_dur	0.0200192	-0.0061392	0.0461776	0.0125402	1.5964015	0.126

How is number of seeds per flower linked to skewness of FFD

```r
kable(prettify(summary(lm(seeds_per_fl ~ FFD_skew,data=data_sel_agg)))) #No effect of FFD_skew
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.623413	0.4241834	0.8226427	0.0955096	6.5272260	<0.001	***
FFD_skew	0.103304	-0.1966666	0.4032745	0.1438043	0.7183648	0.481	

How is number of seeds per flower linked to kurtosis of FFD

```r
kable(prettify(summary(lm(seeds_per_fl ~ FFD_kurt,data=data_sel_agg)))) #No effect of FFD_kurt
```

	Estimate	CI (lower)	CI (upper)	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.5929379	0.1500328	1.0358431	0.2123264	2.7925773	0.011	*
FFD_kurt	0.0216473	-0.1039384	0.1472331	0.0602052	0.3595597	0.723	

SUMMARY

- Phenotypic selection on flowering phenology differs among years (also when including number of flowers in the model)
- There is significant selection for early flowering on 7 out of 22 years studied
- Quadratic selection on flowering phenology is not important (only found in one year)
- Selection for early flowering decreases with precipitation in March and with grazing (although grazing is only significant when included as predictor in a model together with seed predation, fruit set and seed set)
- Grazing increases with precipitation in March and with variance and duration of flowering, and decreases with temperature in April-May
- Seed predation increases with temperature in April-June
- Fruit set increases with variance of flowering
- Seed set increases with precipitation in (April-May-)June
- The number of seeds per flower increases with variance of flowering