Results Lathyrus paper 1

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
```

Calculation of position and duration of flowering season

Calculate proportion of plants flowering per year at each date

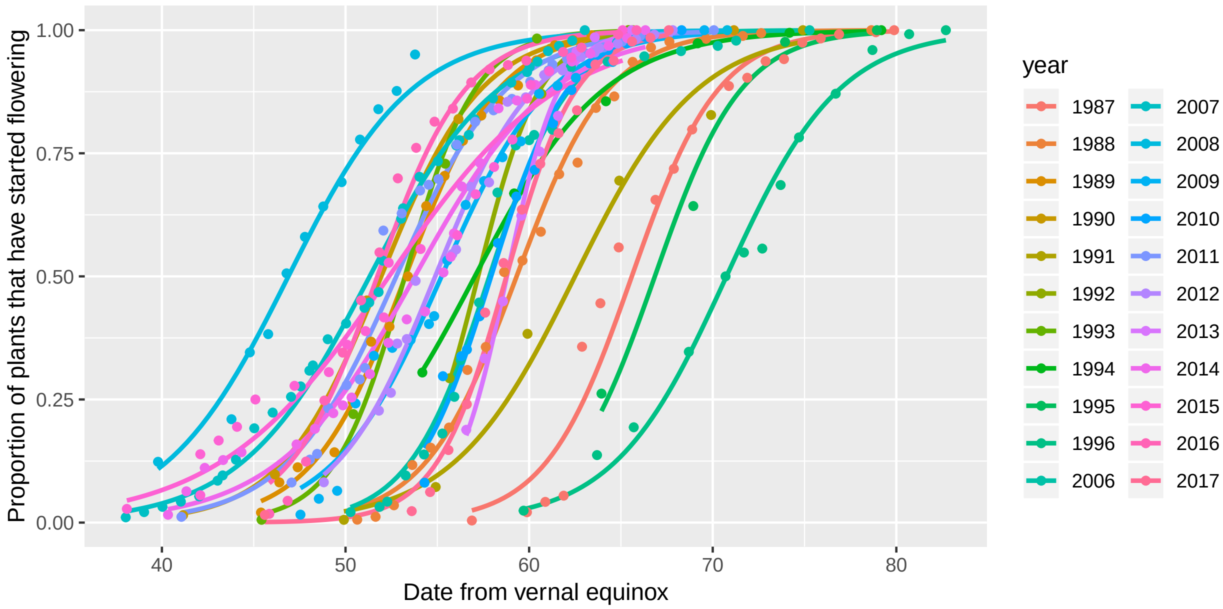
```
propfl<-as.data.frame(aggregate(id~FFD+year,data=alldata_weather_subs[c(1:2,4)],FUN=length) %>%
        group_by(year) %>%
        mutate(n_cum_FFD = cumsum(x = id))) #Cumulated n plants fl per yr at each FFD

max_flowering<-aggregate(n_cum_FFD ~year, data=propfl,FUN=max)
max_flowering$max_flowering<-max_flowering$n_cum_FFD
max_flowering$n_cum_FFD<-NULL

propfl<-merge(propfl,max_flowering)
propfl$prop_fl<-propfl$n_cum_FFD/propfl$max_flowering
```

Models proportion of plants flowering per year against date

```
models_propfl<-propfl %>%
  group_by(year) %>%
  do(model = glm(cbind(n_cum_FFD,max_flowering-n_cum_FFD) ~ FFD, data = .,family=binomial))%>%
  tidy(model)
models_propfl
```

```
## # A tibble: 44 x 6
## # Groups:   year [22]
##    year  term        estimate std.error statistic   p.value
##    <fct> <chr>          <dbl>     <dbl>     <dbl>     <dbl>
##  1 1987  (Intercept)  -27.7      0.808      -34.3 9.89e-258
##  2 1987  FFD            0.422    0.0122      34.5 1.74e-260
```

```
##   3 1988  (Intercept)  -23.6      0.748      -31.5 2.16e-218
##   4 1988  FFD            0.398    0.0126      31.7 4.45e-220
##   5 1989  (Intercept)  -20.9      0.937      -22.3 2.19e-110
##   6 1989  FFD            0.393    0.0174      22.6 5.79e-113
##   7 1990  (Intercept)  -19.1      1.30       -14.7 1.00e- 48
##   8 1990  FFD            0.367    0.0249      14.8 2.71e- 49
##   9 1991  (Intercept)  -18.7      1.06       -17.7 5.22e- 70
##  10 1991  FFD            0.299    0.0169      17.8 1.64e- 70
## # ... with 34 more rows
```



Calculate dates when 10%, 20%, 80% and 90% of plants have started flowering in each year

Dates are calculated using the binomial models (calculations not shown).

```
dates_fl<-data.frame(year=c(1987:1996,2006:2017),date_10,date_20,date_80,date_90)
head(dates_fl)
```

```
##   year  date_10  date_20  date_80  date_90
## 1 1987 60.38876 62.30943 68.87634 70.79705
## 2 1988 53.79735 55.83503 62.80182 64.83949
## 3 1989 47.67251 49.73706 56.79583 58.86038
## 4 1990 45.95380 48.16479 55.72425 57.93525
## 5 1991 55.15323 57.86356 67.13019 69.84053
## 6 1992 55.78171 55.78171 59.57069 60.94629
```

Calculate other metrics of the flowering season and merge

```
fl_pos_dur<-merge(as.data.frame(alldata %>% filter(!is.na(alldata$FFD)) %>%
            dplyr::select(year,FFD)  %>%
            dplyr::group_by(year) %>%
            dplyr::summarise(FFD_mean=mean(FFD),FFD_first=min(FFD), FFD_last=max(FFD),
```

```
                          FFD_var=var(FFD),FFD_dur=range(FFD)[2]-range(FFD)[1],
                          FFD_skew=skewness(FFD),FFD_kurt=kurtosis(FFD))),dates_fl)
fl_pos_dur$days_90_10<-with(fl_pos_dur,date_90-date_10) # Another measure of duration
head(fl_pos_dur)
```

```
##   year FFD_mean FFD_first FFD_last   FFD_var FFD_dur  FFD_skew   FFD_kurt
## 1 1987 66.25589  56.88194 79.88194 16.699234      23 0.8626570  0.2201882
## 2 1988 59.90789  50.63889 78.63889 20.244857      28 0.5791351  0.9320223
## 3 1989 53.85571  45.39653 65.39653 18.807595      20 0.1920443 -0.2264171
## 4 1990 54.46244  41.15417 71.15417 26.093643      30 0.2452248  0.5593864
## 5 1991 64.99514  49.91181 74.91181 36.445531      25 0.2566082 -0.7587831
## 6 1992 59.85048  55.66944 65.66944  9.975637      10 0.1424553 -0.5373083
##    date_10  date_20  date_80  date_90 days_90_10
## 1 60.38876 62.30943 68.87634 70.79705  10.408284
## 2 53.79735 55.83503 62.80182 64.83949  11.042139
## 3 47.67251 49.73706 56.79583 58.86038  11.187872
## 4 45.95380 48.16479 55.72425 57.93525  11.981455
## 5 55.15323 57.86356 67.13019 69.84053  14.687303
## 6 55.78171 55.78171 59.57069 60.94629   5.164579
```

Models of FFD_first, FFD_last, date_10-20-80-90, days_90_10 against weather variables

With FFD_first

```
mean_weather7<-merge(mean_weather6,fl_pos_dur[c(1,3:4,9:13)])
models14<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_first ~ scale(i), list(i = as.name(x))),
                        data = mean_weather7)})
models14_summary<-lapply(X = models14, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models14_summary<-models14_summary[c(1:2,5,6)]
names(models14_summary)<-c("variable","Estimate","P","sig")
models14_summary<-subset(models14_summary,!variable=="(Intercept)")
models14_summary<-cbind(models14_summary,sapply(lapply(X = models14, FUN = summary), "[[", 9))
names(models14_summary)[5]<-"Rsquare"
kable(arrange(subset(models14_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean_b)	-6.103908	<0.001	***	0.6760532
scale(GDD3_34)	-5.968178	<0.001	***	0.6441223
scale(max_b)	-5.946634	<0.001	***	0.6391199
scale(GDH3_34)	-5.871961	<0.001	***	0.6219219
scale(mean_45)	-5.767840	<0.001	***	0.5983041
scale(GDH3_b)	-5.764751	<0.001	***	0.5976101
scale(GDD3_b)	-5.751481	<0.001	***	0.5946319
scale(GDH5_34)	-5.723634	<0.001	***	0.5884048
scale(GDD5_34)	-5.581013	<0.001	***	0.5569857
scale(GDD3_45)	-5.541647	<0.001	***	0.5484532
scale(min_45)	-5.526175	<0.001	***	0.5451160

variable	Estimate	P	sig	Rsquare
scale(max_34)	-5.493885	<0.001	***	0.5381818
scale(GDH3_45)	-5.490866	<0.001	***	0.5375355
scale(max_45)	-5.481160	<0.001	***	0.5354603
scale(GDH5_b)	-5.427729	<0.001	***	0.5241016
scale(GDH7_34)	-5.402895	<0.001	***	0.5188601
scale(mean_4)	-5.307262	<0.001	***	0.4989002
scale(mean_34)	-5.236920	<0.001	***	0.4844465
scale(GDD3_4)	-5.229496	<0.001	***	0.4829323
scale(GDD5_b)	-5.176071	<0.001	***	0.4720991
scale(GDH5_45)	-5.161470	<0.001	***	0.4691576
scale(GDH3_4)	-5.142703	<0.001	***	0.4653893
scale(GDD5_45)	-5.108651	<0.001	***	0.4585866
scale(GDD5_4)	-5.080960	<0.001	***	0.4530880
scale(min_b)	-5.038395	<0.001	***	0.4446942
scale(GDH5_4)	-5.016737	<0.001	***	0.4404504
scale(min_4)	-5.009479	<0.001	***	0.4390323
scale(max_16)	-4.998807	<0.001	***	0.4369509
scale(GDD3_16)	-4.869855	0.001	***	0.4121516
scale(GDH3_16)	-4.836155	0.001	***	0.4057775
scale(GDH7_b)	-4.826718	0.001	***	0.4040004
scale(GDD7_34)	-4.817469	0.001	***	0.4022622
scale(max_4)	-4.794050	0.001	***	0.3978757
scale(GDH7_4)	-4.778104	0.001	**	0.3949012
scale(mean_16)	-4.774932	0.001	**	0.3943107
scale(GDH7_45)	-4.586492	0.002	**	0.3599337
scale(GDH10_34)	-4.582941	0.002	**	0.3592993
scale(GDD7_4)	-4.472055	0.003	**	0.3397327
scale(min_34)	-4.448603	0.003	**	0.3356556
scale(GDH3_3)	-4.411203	0.003	**	0.3291985
scale(mean_46)	-4.407258	0.003	**	0.3285204
scale(GDD3_3)	-4.404001	0.003	**	0.3279613
scale(min_16)	-4.402526	0.003	**	0.3277080
scale(max_46)	-4.370736	0.003	**	0.3222731
scale(max_3)	-4.363559	0.004	**	0.3210514
scale(GDH5_16)	-4.285088	0.004	**	0.3078261
scale(GDD7_45)	-4.272444	0.004	**	0.3057175
scale(GDD3_13)	-4.267057	0.005	**	0.3048211
scale(GDH5_3)	-4.247907	0.005	**	0.3016433
scale(GDH3_13)	-4.243260	0.005	**	0.3008745
scale(GDD7_b)	-4.206784	0.005	**	0.2948679
scale(precipitation_13)	-4.195822	0.005	**	0.2930729
scale(max_13)	-4.171834	0.006	**	0.2891614
scale(mean_13)	-4.143596	0.006	**	0.2845856
scale(GDH5_13)	-4.142648	0.006	**	0.2844326
scale(GDD5_16)	-4.138801	0.006	**	0.2838116
scale(GDD3_46)	-4.100848	0.007	**	0.2777176
scale(mean_3)	-4.094986	0.007	**	0.2767814
scale(GDH10_4)	-4.073755	0.007	**	0.2734016
scale(min_13)	-4.026217	0.008	**	0.2658980
scale(GDH3_46)	-4.002432	0.009	**	0.2621766
scale(GDH7_3)	-3.854263	0.012	*	0.2394911
scale(min_46)	-3.797499	0.014	*	0.2310268

variable	Estimate	P	sig	Rsquare
scale(GDD5_3)	-3.790514	0.014	*	0.2299940
scale(GDD5_13)	-3.755164	0.015	*	0.2247959
scale(GDH7_13)	-3.748279	0.015	*	0.2237891
scale(min_3)	-3.653020	0.018	*	0.2100498
scale(GDH10_b)	-3.621330	0.02	*	0.2055576
scale(GDD5_46)	-3.615456	0.02	*	0.2047291
scale(GDH5_46)	-3.577493	0.021	*	0.1994077
scale(GDH10_45)	-3.542694	0.023	*	0.1945792
scale(GDD10_34)	-3.501712	0.025	*	0.1889534
scale(GDH7_16)	-3.434157	0.028	*	0.1798226
scale(GDD10_4)	-3.106852	0.05	*	0.1381021

With FFD_last

```
models15<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_last ~ scale(i), list(i = as.name(x))),
                          data = mean_weather7)})
models15_summary<-lapply(X = models15, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models15_summary<-models15_summary[c(1:2,5,6)]
names(models15_summary)<-c("variable","Estimate","P","sig")
models15_summary<-subset(models15_summary,!variable=="(Intercept)")
models15_summary<-cbind(models15_summary,sapply(lapply(X = models15, FUN = summary), "[[", 9))
names(models15_summary)[5]<-"Rsquare"
kable(arrange(subset(models15_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(min_5)	-4.510640	<0.001	***	0.5598494
scale(GDH7_45)	-4.506935	<0.001	***	0.5588481
scale(GDH5_45)	-4.491293	<0.001	***	0.5546291
scale(GDD5_45)	-4.462057	<0.001	***	0.5467830
scale(GDD7_45)	-4.429817	<0.001	***	0.5381902
scale(GDH3_45)	-4.394657	<0.001	***	0.5288904
scale(GDD3_45)	-4.358849	<0.001	***	0.5194949
scale(min_45)	-4.311812	<0.001	***	0.5072703
scale(GDH10_45)	-4.301700	<0.001	***	0.5046596
scale(GDH5_5)	-4.265259	<0.001	***	0.4953020
scale(GDH3_16)	-4.264740	<0.001	***	0.4951692
scale(GDH7_5)	-4.259634	<0.001	***	0.4938647
scale(GDH3_5)	-4.254050	<0.001	***	0.4924396
scale(mean_45)	-4.249681	<0.001	***	0.4913260
scale(GDD5_5)	-4.244828	<0.001	***	0.4900905
scale(GDD7_5)	-4.242475	<0.001	***	0.4894917
scale(GDD3_5)	-4.238589	<0.001	***	0.4885039
scale(GDD3_16)	-4.219686	<0.001	***	0.4837114
scale(GDD10_45)	-4.215292	<0.001	***	0.4826005
scale(mean_5)	-4.182338	<0.001	***	0.4743055
scale(GDD10_5)	-4.146113	<0.001	***	0.4652625
scale(GDH10_5)	-4.114950	<0.001	***	0.4575459
scale(GDH5_16)	-4.110689	<0.001	***	0.4564955

variable	Estimate	P	sig	Rsquare
scale(GDD5_16)	-3.997899	0.001	***	0.4290822
scale(GDD3_46)	-3.882864	0.001	***	0.4019086
scale(mean_46)	-3.872485	0.001	***	0.3994959
scale(GDH3_46)	-3.872152	0.001	***	0.3994186
scale(max_5)	-3.866074	0.001	***	0.3980088
scale(max_16)	-3.846577	0.001	**	0.3935016
scale(max_45)	-3.840321	0.001	**	0.3920601
scale(GDD5_46)	-3.824981	0.001	**	0.3885356
scale(GDH5_46)	-3.797762	0.001	**	0.3823164
scale(GDH7_16)	-3.795933	0.001	**	0.3819001
scale(min_46)	-3.768138	0.001	**	0.3755982
scale(GDD7_16)	-3.620926	0.002	**	0.3429937
scale(GDH7_46)	-3.618182	0.003	**	0.3423983
scale(max_46)	-3.602800	0.003	**	0.3390690
scale(max_3)	-3.597444	0.003	**	0.3379131
scale(GDD7_46)	-3.591130	0.003	**	0.3365526
scale(mean_16)	-3.482179	0.004	**	0.3134532
scale(mean_b)	-3.319274	0.007	**	0.2802422
scale(max_34)	-3.278196	0.007	**	0.2721189
scale(GDH10_16)	-3.241990	0.008	**	0.2650428
scale(GDH3_3)	-3.217362	0.009	**	0.2602745
scale(GDH10_46)	-3.187718	0.01	**	0.2545834
scale(GDH3_13)	-3.178015	0.01	**	0.2527319
scale(GDH3_b)	-3.164582	0.01	*	0.2501780
scale(GDD3_b)	-3.151599	0.011	*	0.2477201
scale(GDD3_3)	-3.142863	0.011	*	0.2460720
scale(max_b)	-3.133708	0.011	*	0.2443495
scale(max_13)	-3.093156	0.013	*	0.2367806
scale(GDD10_16)	-3.090531	0.013	*	0.2362942
scale(GDD3_13)	-3.089528	0.013	*	0.2361084
scale(GDD10_46)	-3.088169	0.013	*	0.2358567
scale(mean_3)	-3.086984	0.013	*	0.2356374
scale(min_16)	-3.053517	0.014	*	0.2294776
scale(mean_34)	-3.049881	0.014	*	0.2288125
scale(GDH5_b)	-3.025428	0.015	*	0.2243595
scale(GDD5_b)	-2.944207	0.018	*	0.2098263
scale(GDH5_13)	-2.880970	0.022	*	0.1987848
scale(GDH3_34)	-2.833682	0.024	*	0.1906847
scale(GDD3_34)	-2.806325	0.026	*	0.1860599
scale(GDH5_3)	-2.805960	0.026	*	0.1859986
scale(GDH7_b)	-2.800757	0.026	*	0.1851240
scale(mean_13)	-2.780684	0.027	*	0.1817659
scale(min_b)	-2.701016	0.033	*	0.1686758
scale(min_3)	-2.576678	0.043	*	0.1490062
scale(min_34)	-2.543446	0.046	*	0.1439061
scale(GDD7_b)	-2.543048	0.046	*	0.1438454
scale(min_13)	-2.506245	0.05	*	0.1382753

With date_10

```
models16<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(date_10 ~ scale(i), list(i = as.name(x))),
                          data = mean_weather7)})
models16_summary<-lapply(X = models16, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models16_summary<-models16_summary[c(1:2,5,6)]
names(models16_summary)<-c("variable","Estimate","P","sig")
models16_summary<-subset(models16_summary,!variable=="(Intercept)")
models16_summary<-cbind(models16_summary,sapply(lapply(X = models16, FUN = summary), "[[", 9))
names(models16_summary)[5]<-"Rsquare"
kable(arrange(subset(models16_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean_45)	-5.609292	<0.001	***	0.7023764
scale(mean_b)	-5.525249	<0.001	***	0.6799997
scale(min_45)	-5.382888	<0.001	***	0.6428667
scale(GDD3_45)	-5.371391	<0.001	***	0.6399102
scale(GDD3_b)	-5.363048	<0.001	***	0.6377688
scale(max_45)	-5.325682	<0.001	***	0.6282183
scale(GDH3_b)	-5.325520	<0.001	***	0.6281770
scale(GDH3_45)	-5.310196	<0.001	***	0.6242797
scale(max_b)	-5.302125	<0.001	***	0.6222317
scale(GDH5_b)	-5.036591	<0.001	***	0.5565859
scale(GDD3_34)	-5.013581	<0.001	***	0.5510562
scale(GDH5_45)	-5.000905	<0.001	***	0.5480208
scale(GDD5_45)	-4.946429	<0.001	***	0.5350629
scale(GDH3_34)	-4.908166	<0.001	***	0.5260465
scale(GDD5_b)	-4.868289	<0.001	***	0.5167242
scale(GDD3_16)	-4.742488	<0.001	***	0.4878133
scale(max_16)	-4.709113	<0.001	***	0.4802702
scale(GDH3_16)	-4.693240	<0.001	***	0.4767014
scale(min_b)	-4.679390	<0.001	***	0.4735975
scale(max_34)	-4.661398	<0.001	***	0.4695787
scale(GDH5_34)	-4.653344	<0.001	***	0.4677849
scale(min_4)	-4.631395	<0.001	***	0.4629117
scale(mean_4)	-4.590518	<0.001	***	0.4538978
scale(GDH7_b)	-4.535646	<0.001	***	0.4419232
scale(mean_34)	-4.525262	<0.001	***	0.4396732
scale(max_46)	-4.519119	<0.001	***	0.4383448
scale(mean_46)	-4.502448	0.001	***	0.4347485
scale(GDD5_34)	-4.500811	0.001	***	0.4343961
scale(GDH7_45)	-4.479617	0.001	***	0.4298448
scale(mean_16)	-4.443113	0.001	***	0.4220563
scale(GDD3_4)	-4.436783	0.001	***	0.4207121
scale(GDH3_4)	-4.333740	0.001	***	0.3991017
scale(GDH7_34)	-4.302026	0.001	**	0.3925528
scale(GDD7_45)	-4.223716	0.001	**	0.3765878
scale(GDH5_16)	-4.212508	0.001	**	0.3743268
scale(GDD3_46)	-4.211584	0.001	**	0.3741407
scale(GDD5_4)	-4.139377	0.002	**	0.3597216
scale(GDH5_4)	-4.138168	0.002	**	0.3594825

variable	Estimate	P	sig	Rsquare
scale(GDH3_46)	-4.113352	0.002	**	0.3545859
scale(GDD5_16)	-4.088070	0.002	**	0.3496278
scale(GDD7_b)	-4.067765	0.002	**	0.3456678
scale(min_16)	-4.033000	0.003	**	0.3389336
scale(max_4)	-3.999222	0.003	**	0.3324460
scale(min_34)	-3.936563	0.004	**	0.3205557
scale(GDH7_4)	-3.872536	0.004	**	0.3085997
scale(GDD7_34)	-3.839761	0.005	**	0.3025553
scale(min_46)	-3.837762	0.005	**	0.3021884
scale(GDD3_13)	-3.753343	0.006	**	0.2868647
scale(precipitation_13)	-3.752029	0.006	**	0.2866289
scale(GDD5_46)	-3.749015	0.006	**	0.2860883
scale(max_13)	-3.747423	0.006	**	0.2858029
scale(max_3)	-3.746788	0.006	**	0.2856891
scale(GDH3_13)	-3.740661	0.006	**	0.2845921
scale(GDH5_46)	-3.721209	0.007	**	0.2811214
scale(mean_13)	-3.716385	0.007	**	0.2802634
scale(GDH3_3)	-3.647065	0.008	**	0.2680578
scale(GDD3_3)	-3.643690	0.008	**	0.2674694
scale(GDD7_4)	-3.607219	0.009	**	0.2611459
scale(min_13)	-3.602717	0.009	**	0.2603697
scale(GDH10_34)	-3.555027	0.01	*	0.2522073
scale(mean_3)	-3.536272	0.011	*	0.2490270
scale(GDH10_45)	-3.525101	0.011	*	0.2471407
scale(GDH10_b)	-3.501433	0.011	*	0.2431640
scale(GDH7_16)	-3.492608	0.012	*	0.2416882
scale(GDH5_13)	-3.462076	0.013	*	0.2366106
scale(GDH5_3)	-3.366089	0.016	*	0.2209381
scale(mean_5)	-3.302640	0.018	*	0.2108203
scale(GDD3_5)	-3.251299	0.02	*	0.2027743
scale(GDD7_16)	-3.218828	0.022	*	0.1977505
scale(GDH10_4)	-3.216880	0.022	*	0.1974507
scale(GDH3_5)	-3.210184	0.022	*	0.1964216
scale(max_5)	-3.196151	0.023	*	0.1942719
scale(GDD5_5)	-3.194765	0.023	*	0.1940602
scale(GDH7_46)	-3.171379	0.024	*	0.1905001
scale(min_3)	-3.163497	0.025	*	0.1893061
scale(min_5)	-3.108100	0.028	*	0.1809984
scale(GDH5_5)	-3.106551	0.028	*	0.1807683
scale(GDD5_13)	-3.061536	0.03	*	0.1741289
scale(GDD7_46)	-3.046592	0.031	*	0.1719461
scale(GDD5_3)	-2.984799	0.035	*	0.1630341
scale(GDD7_5)	-2.958619	0.037	*	0.1593134
scale(GDH7_13)	-2.947866	0.038	*	0.1577947
scale(GDH7_3)	-2.939229	0.039	*	0.1565788
scale(GDH7_5)	-2.904674	0.041	*	0.1517501
scale(GDD10_34)	-2.834436	0.047	*	0.1421111

With date_20

```
models17<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(date_20 ~ scale(i), list(i = as.name(x))),
                          data = mean_weather7)})
models17_summary<-lapply(X = models17, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models17_summary<-models17_summary[c(1:2,5,6)]
names(models17_summary)<-c("variable","Estimate","P","sig")
models17_summary<-subset(models17_summary,!variable=="(Intercept)")
models17_summary<-cbind(models17_summary,sapply(lapply(X = models17, FUN = summary), "[[", 9))
names(models17_summary)[5]<-"Rsquare"
kable(arrange(subset(models17_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean_45)	-5.304641	<0.001	***	0.7488650
scale(GDD3_45)	-5.082933	<0.001	***	0.6834830
scale(min_45)	-5.080096	<0.001	***	0.6826647
scale(mean_b)	-5.051815	<0.001	***	0.6745299
scale(GDH3_45)	-5.033528	<0.001	***	0.6692938
scale(max_45)	-5.019049	<0.001	***	0.6651618
scale(GDD3_b)	-4.933349	<0.001	***	0.6409474
scale(GDH3_b)	-4.897249	<0.001	***	0.6308725
scale(max_b)	-4.850269	<0.001	***	0.6178717
scale(GDH5_45)	-4.793629	<0.001	***	0.6023644
scale(GDD5_45)	-4.734707	<0.001	***	0.5864255
scale(GDH5_b)	-4.671399	<0.001	***	0.5695199
scale(GDD3_16)	-4.596247	<0.001	***	0.5497469
scale(GDH3_16)	-4.554746	<0.001	***	0.5389654
scale(GDD5_b)	-4.529060	<0.001	***	0.5323412
scale(max_16)	-4.496285	<0.001	***	0.5239434
scale(max_46)	-4.444193	<0.001	***	0.5107214
scale(mean_46)	-4.433625	<0.001	***	0.5080580
scale(GDD3_34)	-4.389811	<0.001	***	0.4970827
scale(GDH7_45)	-4.378863	<0.001	***	0.4943573
scale(GDH3_34)	-4.296344	<0.001	***	0.4740339
scale(GDH7_b)	-4.280149	<0.001	***	0.4700907
scale(min_b)	-4.248920	<0.001	***	0.4625291
scale(mean_16)	-4.207527	<0.001	***	0.4525915
scale(GDD3_46)	-4.175745	<0.001	***	0.4450275
scale(GDD7_45)	-4.162683	<0.001	***	0.4419355
scale(GDH5_16)	-4.159465	<0.001	***	0.4411751
scale(max_34)	-4.149316	<0.001	***	0.4387811
scale(min_4)	-4.140371	<0.001	***	0.4366758
scale(GDH3_46)	-4.092908	0.001	***	0.4255819
scale(mean_34)	-4.053436	0.001	***	0.4164532
scale(GDD5_16)	-4.045154	0.001	***	0.4145489
scale(GDH5_34)	-4.014749	0.001	***	0.4075917
scale(mean_4)	-3.994912	0.001	***	0.4030810
scale(GDD7_b)	-3.890528	0.001	**	0.3797130
scale(GDD5_34)	-3.869625	0.001	**	0.3751078
scale(GDD3_4)	-3.823607	0.002	**	0.3650570
scale(min_46)	-3.793420	0.002	**	0.3585293

variable	Estimate	P	sig	Rsquare
scale(GDD5_46)	-3.782681	0.002	**	0.3562194
scale(min_16)	-3.778393	0.002	**	0.3552990
scale(GDH5_46)	-3.765321	0.002	**	0.3524994
scale(GDH3_4)	-3.718213	0.003	**	0.3424912
scale(GDH7_34)	-3.680089	0.003	**	0.3344837
scale(GDH10_45)	-3.588484	0.004	**	0.3155809
scale(GDH7_16)	-3.561914	0.004	**	0.3101871
scale(min_34)	-3.555382	0.004	**	0.3088673
scale(GDH5_4)	-3.522998	0.005	**	0.3023597
scale(max_13)	-3.515541	0.005	**	0.3008696
scale(GDD5_4)	-3.515143	0.005	**	0.3007901
scale(GDH3_13)	-3.464158	0.006	**	0.2906879
scale(GDD3_13)	-3.464149	0.006	**	0.2906861
scale(mean_13)	-3.456817	0.006	**	0.2892456
scale(mean_5)	-3.447991	0.006	**	0.2875155
scale(max_3)	-3.436382	0.006	**	0.2852465
scale(GDH10_b)	-3.425894	0.006	**	0.2832032
scale(max_4)	-3.404147	0.007	**	0.2789865
scale(GDD3_5)	-3.379665	0.007	**	0.2742714
scale(max_5)	-3.379038	0.007	**	0.2741511
scale(precipitation_13)	-3.366027	0.008	**	0.2716597
scale(GDH3_5)	-3.345352	0.008	**	0.2677202
scale(GDD5_5)	-3.333036	0.008	**	0.2653853
scale(GDD7_16)	-3.330017	0.008	**	0.2648141
scale(min_13)	-3.324774	0.008	**	0.2638236
scale(GDH7_46)	-3.302618	0.009	**	0.2596551
scale(GDD7_34)	-3.294086	0.009	**	0.2580570
scale(GDH7_4)	-3.285560	0.009	**	0.2564645
scale(GDH3_3)	-3.278406	0.01	**	0.2551313
scale(GDD3_3)	-3.268543	0.01	**	0.2532981
scale(GDH5_5)	-3.261869	0.01	*	0.2520609
scale(mean_3)	-3.226031	0.011	*	0.2454598
scale(GDD7_46)	-3.194596	0.012	*	0.2397298
scale(GDH5_13)	-3.146706	0.014	*	0.2311084
scale(min_5)	-3.140416	0.014	*	0.2299856
scale(GDD7_5)	-3.125652	0.014	*	0.2273592
scale(GDH7_5)	-3.091937	0.016	*	0.2214079
scale(GDD7_4)	-3.079979	0.016	*	0.2193127
scale(GDH10_34)	-3.032710	0.018	*	0.2111098
scale(GDH5_3)	-2.973613	0.021	*	0.2010327
scale(min_3)	-2.871978	0.026	*	0.1841658
scale(GDD10_45)	-2.843882	0.028	*	0.1796068
scale(GDD5_13)	-2.763541	0.034	*	0.1668169
scale(GDH10_5)	-2.737903	0.036	*	0.1628127
scale(GDH10_4)	-2.733017	0.036	*	0.1620537
scale(GDH10_16)	-2.691537	0.039	*	0.1556658
scale(GDD5_3)	-2.641555	0.043	*	0.1480983
scale(GDH7_13)	-2.628514	0.045	*	0.1461472
scale(GDH10_46)	-2.596006	0.048	*	0.1413254

With date_80

```
models18<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(date_80 ~ scale(i), list(i = as.name(x))),
                          data = mean_weather7)})
models18_summary<-lapply(X = models18, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models18_summary<-models18_summary[c(1:2,5,6)]
names(models18_summary)<-c("variable","Estimate","P","sig")
models18_summary<-subset(models18_summary,!variable=="(Intercept)")
models18_summary<-cbind(models18_summary,sapply(lapply(X = models18, FUN = summary), "[[", 9))
names(models18_summary)[5]<-"Rsquare"
kable(arrange(subset(models18_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean_45)	-4.886031	<0.001	***	0.7791540
scale(GDD3_45)	-4.792512	<0.001	***	0.7477174
scale(GDH3_45)	-4.782490	<0.001	***	0.7443847
scale(GDH5_45)	-4.754108	<0.001	***	0.7349839
scale(GDD5_45)	-4.714959	<0.001	***	0.7221088
scale(min_45)	-4.651202	<0.001	***	0.7013687
scale(GDH7_45)	-4.625914	<0.001	***	0.6932207
scale(max_45)	-4.610132	<0.001	***	0.6881582
scale(GDD3_16)	-4.541063	<0.001	***	0.6662057
scale(GDD7_45)	-4.513680	<0.001	***	0.6575940
scale(GDH3_16)	-4.507984	<0.001	***	0.6558092
scale(mean_46)	-4.471568	<0.001	***	0.6444521
scale(max_46)	-4.429332	<0.001	***	0.6313953
scale(GDH5_16)	-4.342895	<0.001	***	0.6050604
scale(GDD3_46)	-4.331809	<0.001	***	0.6017202
scale(mean_5)	-4.316552	<0.001	***	0.5971376
scale(max_5)	-4.314047	<0.001	***	0.5963866
scale(GDH3_46)	-4.287641	<0.001	***	0.5884980
scale(GDD5_16)	-4.279888	<0.001	***	0.5861910
scale(GDD3_5)	-4.254152	<0.001	***	0.5785628
scale(GDH10_45)	-4.239341	<0.001	***	0.5741938
scale(GDH3_5)	-4.237401	<0.001	***	0.5736224
scale(GDD3_b)	-4.235220	<0.001	***	0.5729807
scale(GDD5_5)	-4.233961	<0.001	***	0.5726104
scale(GDH3_b)	-4.206094	<0.001	***	0.5644415
scale(GDH5_5)	-4.194005	<0.001	***	0.5609146
scale(mean_b)	-4.188906	<0.001	***	0.5594301
scale(GDH5_b)	-4.173152	<0.001	***	0.5548547
scale(GDD5_46)	-4.145354	<0.001	***	0.5468236
scale(GDH5_46)	-4.125117	<0.001	***	0.5410106
scale(GDD5_b)	-4.121912	<0.001	***	0.5400924
scale(max_16)	-4.113530	<0.001	***	0.5376949
scale(GDD7_5)	-4.091047	<0.001	***	0.5312882
scale(GDH7_5)	-4.087710	<0.001	***	0.5303405
scale(GDH7_b)	-4.067070	<0.001	***	0.5244946
scale(max_b)	-4.032612	<0.001	***	0.5148011
scale(GDH7_16)	-4.015607	<0.001	***	0.5100477
scale(min_46)	-3.917565	<0.001	***	0.4830341

variable	Estimate	P	sig	Rsquare
scale(GDD7_16)	-3.884384	<0.001	***	0.4740431
scale(GDH7_46)	-3.860158	<0.001	***	0.4675267
scale(GDD7_b)	-3.855158	<0.001	***	0.4661869
scale(min_5)	-3.850984	<0.001	***	0.4650698
scale(GDH10_5)	-3.822571	<0.001	***	0.4574974
scale(GDD7_46)	-3.804748	<0.001	***	0.4527760
scale(GDD10_45)	-3.802173	<0.001	***	0.4520957
scale(mean_16)	-3.754825	<0.001	***	0.4396684
scale(GDH10_b)	-3.630432	0.001	***	0.4077616
scale(GDD10_5)	-3.533529	0.001	**	0.3836507
scale(GDH10_16)	-3.446255	0.002	**	0.3624939
scale(min_b)	-3.411415	0.002	**	0.3541957
scale(GDH10_46)	-3.379851	0.002	**	0.3467507
scale(min_16)	-3.254903	0.004	**	0.3179583
scale(GDD10_16)	-3.111827	0.006	**	0.2863206
scale(GDD10_46)	-3.092343	0.006	**	0.2821222
scale(max_13)	-3.043923	0.008	**	0.2718028
scale(GDD3_13)	-3.042196	0.008	**	0.2714378
scale(GDH3_13)	-3.038950	0.008	**	0.2707523
scale(GDD10_b)	-3.025818	0.008	**	0.2679862
scale(GDD3_34)	-2.990606	0.009	**	0.2606283
scale(GDH3_34)	-2.905369	0.011	*	0.2431739
scale(mean_13)	-2.898273	0.012	*	0.2417435
scale(max_34)	-2.886996	0.012	*	0.2394778
scale(mean_34)	-2.841236	0.014	*	0.2303738
scale(GDH5_13)	-2.706629	0.02	*	0.2044370
scale(min_4)	-2.705104	0.02	*	0.2041503
scale(min_13)	-2.700853	0.02	*	0.2033522
scale(max_3)	-2.680203	0.021	*	0.1994928
scale(GDD3_3)	-2.636802	0.024	*	0.1914781
scale(GDH3_3)	-2.612213	0.025	*	0.1869953
scale(GDH5_34)	-2.596949	0.026	*	0.1842338
scale(GDD5_34)	-2.504409	0.033	*	0.1678377
scale(min_34)	-2.481947	0.035	*	0.1639477
scale(mean_4)	-2.463259	0.037	*	0.1607380
scale(mean_3)	-2.429688	0.039	*	0.1550330
scale(GDD5_13)	-2.402659	0.042	*	0.1504965
scale(GDH5_3)	-2.338815	0.048	*	0.1399829

With date_90

```
models19<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(date_90 ~ scale(i), list(i = as.name(x))),
                          data = mean_weather7)})
models19_summary<-lapply(X = models19, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models19_summary<-models19_summary[c(1:2,5,6)]
names(models19_summary)<-c("variable","Estimate","P","sig")
models19_summary<-subset(models19_summary,!variable=="(Intercept)")
models19_summary<-cbind(models19_summary,sapply(lapply(X = models19, FUN = summary), "[[", 9))
```

```r
names(models19_summary)[5]<-"Rsquare"
kable(arrange(subset(models19_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean_45)	-4.780968	<0.001	***	0.7464281
scale(GDH5_45)	-4.768925	<0.001	***	0.7424209
scale(GDD5_45)	-4.735733	<0.001	***	0.7314288
scale(GDH3_45)	-4.733345	<0.001	***	0.7306408
scale(GDD3_45)	-4.730538	<0.001	***	0.7297153
scale(GDH7_45)	-4.725221	<0.001	***	0.7279636
scale(GDD7_45)	-4.642303	<0.001	***	0.7008996
scale(max_5)	-4.602059	<0.001	***	0.6879369
scale(mean_5)	-4.588322	<0.001	***	0.6835382
scale(min_45)	-4.540131	<0.001	***	0.6682103
scale(GDD3_16)	-4.539823	<0.001	***	0.6681129
scale(GDD3_5)	-4.532186	<0.001	***	0.6656989
scale(GDH3_5)	-4.521116	<0.001	***	0.6622070
scale(GDD5_5)	-4.520168	<0.001	***	0.6619086
scale(max_45)	-4.511601	<0.001	***	0.6592125
scale(GDH3_16)	-4.509169	<0.001	***	0.6584482
scale(mean_46)	-4.492335	<0.001	***	0.6531683
scale(GDH5_5)	-4.489746	<0.001	***	0.6523579
scale(GDH10_45)	-4.456266	<0.001	***	0.6419221
scale(max_46)	-4.434144	<0.001	***	0.6350694
scale(GDH5_16)	-4.413710	<0.001	***	0.6287699
scale(GDH7_5)	-4.402538	<0.001	***	0.6253379
scale(GDD7_5)	-4.398666	<0.001	***	0.6241505
scale(GDD3_46)	-4.390457	<0.001	***	0.6216367
scale(GDD5_16)	-4.366589	<0.001	***	0.6143542
scale(GDH3_46)	-4.358142	<0.001	***	0.6117863
scale(GDD5_46)	-4.265769	<0.001	***	0.5840298
scale(GDH5_46)	-4.244093	<0.001	***	0.5776027
scale(GDH10_5)	-4.164493	<0.001	***	0.5542814
scale(GDH7_16)	-4.163759	<0.001	***	0.5540683
scale(GDD10_45)	-4.110401	<0.001	***	0.5386855
scale(min_5)	-4.091547	<0.001	***	0.5332975
scale(GDD7_16)	-4.060930	<0.001	***	0.5246005
scale(GDD3_b)	-4.051381	<0.001	***	0.5219015
scale(GDH5_b)	-4.050217	<0.001	***	0.5215727
scale(GDH7_46)	-4.035462	<0.001	***	0.5174157
scale(GDH7_b)	-4.026263	<0.001	***	0.5148319
scale(GDH3_b)	-4.025277	<0.001	***	0.5145554
scale(GDD5_b)	-4.024906	<0.001	***	0.5144512
scale(max_16)	-4.007816	<0.001	***	0.5096679
scale(GDD7_46)	-3.995372	<0.001	***	0.5061981
scale(min_46)	-3.966258	<0.001	***	0.4981215
scale(mean_b)	-3.952909	<0.001	***	0.4944382
scale(GDD10_5)	-3.886912	<0.001	***	0.4764102
scale(GDD7_b)	-3.863227	<0.001	***	0.4700145
scale(max_b)	-3.811781	<0.001	***	0.4562567
scale(GDH10_b)	-3.708891	0.001	***	0.4292951
scale(GDH10_16)	-3.676291	0.001	***	0.4209065
scale(mean_16)	-3.628740	0.001	***	0.4088033

variable	Estimate	P	sig	Rsquare
scale(GDH10_46)	-3.616994	0.001	***	0.4058380
scale(GDD10_16)	-3.387460	0.002	**	0.3498189
scale(GDD10_46)	-3.370005	0.002	**	0.3457091
scale(GDD10_b)	-3.207245	0.004	**	0.3084093
scale(min_b)	-3.175444	0.005	**	0.3013370
scale(min_16)	-3.107722	0.006	**	0.2865110
scale(GDD3_13)	-2.930996	0.01	*	0.2493267
scale(GDH3_13)	-2.925578	0.011	*	0.2482210
scale(max_13)	-2.909480	0.011	*	0.2449481
scale(mean_13)	-2.739041	0.018	*	0.2114039
scale(GDD3_34)	-2.596743	0.026	*	0.1849487
scale(GDH5_13)	-2.596269	0.026	*	0.1848628
scale(max_34)	-2.526502	0.031	*	0.1724099
scale(min_13)	-2.521991	0.031	*	0.1716165
scale(GDH3_34)	-2.513398	0.032	*	0.1701089
scale(mean_34)	-2.487120	0.034	*	0.1655304
scale(GDD3_3)	-2.469574	0.036	*	0.1625001
scale(max_3)	-2.461834	0.036	*	0.1611702
scale(GDH3_3)	-2.432732	0.039	*	0.1562070
scale(precipitation_5)	2.324265	0.05	*	0.1382289

With days_90_10

```
models20<-lapply(names(mean_weather7)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(days_90_10 ~ scale(i), list(i = as.name(x))),
                        data = mean_weather7)})
models20_summary<-lapply(X = models20, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models20_summary<-models20_summary[c(1:2,5,6)]
names(models20_summary)<-c("variable","Estimate","P","sig")
models20_summary<-subset(models20_summary,!variable=="(Intercept)")
models20_summary<-cbind(models20_summary,sapply(lapply(X = models20, FUN = summary), "[[", 9))
names(models20_summary)[5]<-"Rsquare"
kable(arrange(subset(models20_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(GDH3_4)	2.609587	<0.001	***	0.4926759
scale(GDD3_4)	2.594391	<0.001	***	0.4863741
scale(GDH5_4)	2.577190	<0.001	***	0.4792852
scale(mean_4)	2.569025	<0.001	***	0.4759370
scale(GDD5_4)	2.552054	<0.001	***	0.4690110
scale(max_4)	2.494973	<0.001	***	0.4460537
scale(GDH5_34)	2.451434	0.001	***	0.4288916
scale(GDH7_4)	2.436748	0.001	***	0.4231710
scale(GDD3_34)	2.416838	0.001	***	0.4154703
scale(GDH3_34)	2.394768	0.001	***	0.4070079
scale(GDH7_34)	2.382928	0.001	***	0.4025001
scale(GDD5_34)	2.374691	0.001	***	0.3993775
scale(min_4)	2.360905	0.001	**	0.3941750
scale(GDD7_4)	2.239838	0.002	**	0.3497883

variable	Estimate	P	sig	Rsquare
scale(GDD7_34)	2.143644	0.004	**	0.3161863
scale(max_34)	2.134896	0.004	**	0.3132039
scale(precipitation_13)	2.043201	0.006	**	0.2826741
scale(mean_34)	2.038141	0.007	**	0.2810286
scale(GDH10_34)	2.024376	0.007	**	0.2765723
scale(GDH10_4)	2.014481	0.007	**	0.2733876
scale(min_34)	1.779925	0.021	*	0.2024645
scale(precipitation_4)	-1.753201	0.023	*	0.1949405
scale(GDD10_5)	-1.716217	0.026	*	0.1847153
scale(GDH10_5)	-1.660582	0.032	*	0.1697443
scale(precipitation_3)	1.623650	0.037	*	0.1600787
scale(mean_b)	1.572340	0.044	*	0.1470107

Selection differentials for each year

FFD, linear

```
seldiffs_FFD<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std, data = .)) %>% tidy(model))
seldiffs_FFD_nobs<-data.frame(data_sel %>% group_by(year) %>%
  do(nobs = nobs(lm(n_intact_seeds_rel ~ FFD_std, data = .)))) #N observations for each year
seldiffs_FFD_nobs
```

```
##    year nobs
## 1  1987  238
## 2  1988  171
## 3  1989   98
## 4  1990  133
## 5  1991  180
## 6  1992  116
## 7  1993  177
## 8  1994  187
## 9  1995   42
## 10 1996  124
## 11 2006   94
## 12 2007   94
## 13 2008   81
## 14 2009   61
## 15 2010   74
## 16 2011   86
## 17 2012  110
## 18 2013   69
## 19 2014   63
## 20 2015   36
## 21 2016  111
## 22 2017  129
```

```
seldiffs_FFD$sig<-ifelse(seldiffs_FFD$p.value<0.05,"*","")
kable(subset(seldiffs_FFD,term=="FFD_std"),digits=3)  #Linear selection differentials for FFD
```

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	FFD_std	-0.372	0.092	-4.052	0.000	*
4	1988	FFD_std	-0.302	0.106	-2.840	0.005	*
6	1989	FFD_std	-0.609	0.128	-4.767	0.000	*
8	1990	FFD_std	-0.469	0.162	-2.887	0.005	*
10	1991	FFD_std	-0.662	0.078	-8.495	0.000	*
12	1992	FFD_std	-0.438	0.183	-2.391	0.018	*
14	1993	FFD_std	-0.428	0.133	-3.227	0.001	*
16	1994	FFD_std	-0.429	0.180	-2.387	0.018	*
18	1995	FFD_std	-0.147	0.241	-0.607	0.547	
20	1996	FFD_std	-0.373	0.106	-3.512	0.001	*
22	2006	FFD_std	-0.396	0.135	-2.920	0.004	*
24	2007	FFD_std	-0.425	0.111	-3.839	0.000	*
26	2008	FFD_std	-0.512	0.121	-4.247	0.000	*
28	2009	FFD_std	-0.215	0.269	-0.800	0.427	
30	2010	FFD_std	-0.492	0.164	-3.008	0.004	*
32	2011	FFD_std	-0.709	0.196	-3.609	0.001	*
34	2012	FFD_std	-1.035	0.187	-5.532	0.000	*
36	2013	FFD_std	-0.425	0.322	-1.319	0.192	
38	2014	FFD_std	-0.668	0.173	-3.854	0.000	*
40	2015	FFD_std	0.048	0.231	0.208	0.837	
42	2016	FFD_std	-0.351	0.096	-3.664	0.000	*
44	2017	FFD_std	0.282	0.497	0.567	0.572	

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

FFD, quadratic

```
seldiffs_FFD_q<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std+I(FFD_std^2), data = .)) %>% tidy(model))
seldiffs_FFD_q$sig<-ifelse(seldiffs_FFD_q$p.value<0.05,"*","")
kable(subset(seldiffs_FFD_q,term=="I(FFD_std^2)"),digits=3)  #Quadratic selection differentials for FFD
```

	year	term	estimate	std.error	statistic	p.value	sig
3	1987	I(FFD_std^2)	-0.027	0.076	-0.348	0.728	
6	1988	I(FFD_std^2)	-0.030	0.067	-0.444	0.658	
9	1989	I(FFD_std^2)	0.067	0.099	0.673	0.502	
12	1990	I(FFD_std^2)	0.060	0.105	0.574	0.567	
15	1991	I(FFD_std^2)	0.087	0.072	1.200	0.232	
18	1992	I(FFD_std^2)	0.014	0.155	0.092	0.927	
21	1993	I(FFD_std^2)	-0.039	0.105	-0.376	0.707	
24	1994	I(FFD_std^2)	0.028	0.150	0.187	0.852	
27	1995	I(FFD_std^2)	-0.174	0.247	-0.703	0.486	
30	1996	I(FFD_std^2)	-0.089	0.089	-0.997	0.321	
33	2006	I(FFD_std^2)	0.075	0.073	1.016	0.312	
36	2007	I(FFD_std^2)	0.090	0.097	0.926	0.357	
39	2008	I(FFD_std^2)	0.164	0.063	2.595	0.011	*
42	2009	I(FFD_std^2)	-0.203	0.234	-0.866	0.390	
45	2010	I(FFD_std^2)	0.141	0.142	0.994	0.324	
48	2011	I(FFD_std^2)	0.191	0.134	1.425	0.158	

	year	term	estimate	std.error	statistic	p.value	sig
51	2012	I(FFD_std^2)	0.560	0.138	4.063	0.000	*
54	2013	I(FFD_std^2)	0.003	0.303	0.011	0.992	
57	2014	I(FFD_std^2)	0.177	0.143	1.241	0.219	
60	2015	I(FFD_std^2)	-0.423	0.237	-1.783	0.084	
63	2016	I(FFD_std^2)	0.008	0.068	0.112	0.911	
66	2017	I(FFD_std^2)	-0.125	0.250	-0.497	0.620	

```
#I(FFD_std^2) * (disruptive selection - increases variance) in 2008 and 2012
```

Number of flowers, linear

```
seldiffs_nfl<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ n_fl_std, data = .)) %>% tidy(model))
seldiffs_nfl$sig<-ifelse(seldiffs_nfl$p.value<0.05,"*","")
kable(subset(seldiffs_nfl,term=="n_fl_std"),digits=3)  #Linear selection differentials for nfl
```

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	n_fl_std	0.766	0.081	9.478	0.000	*
4	1988	n_fl_std	0.541	0.101	5.376	0.000	*
6	1989	n_fl_std	0.846	0.113	7.504	0.000	*
8	1990	n_fl_std	0.681	0.156	4.357	0.000	*
10	1991	n_fl_std	0.695	0.076	9.104	0.000	*
12	1992	n_fl_std	0.114	0.187	0.606	0.546	
14	1993	n_fl_std	0.436	0.133	3.285	0.001	*
16	1994	n_fl_std	0.449	0.180	2.498	0.013	*
18	1995	n_fl_std	0.364	0.236	1.545	0.130	
20	1996	n_fl_std	0.642	0.095	6.750	0.000	*
22	2006	n_fl_std	0.611	0.126	4.835	0.000	*
24	2007	n_fl_std	0.283	0.116	2.445	0.016	*
26	2008	n_fl_std	0.769	0.102	7.541	0.000	*
28	2009	n_fl_std	0.304	0.267	1.137	0.260	
30	2010	n_fl_std	0.280	0.170	1.644	0.104	
32	2011	n_fl_std	0.924	0.185	4.985	0.000	*
34	2012	n_fl_std	1.054	0.186	5.666	0.000	*
36	2013	n_fl_std	0.083	0.326	0.255	0.800	
38	2014	n_fl_std	0.252	0.191	1.324	0.190	
40	2015	n_fl_std	-0.003	0.231	-0.012	0.990	
42	2016	n_fl_std	0.606	0.083	7.267	0.000	*
44	2017	n_fl_std	-0.541	0.496	-1.091	0.277	

```
#nfl * (selection for high number of flowers) in all years but 1992,1995,2009,2010,2013,2014,2015,2017
```

Number of flowers, quadratic

```
seldiffs_nfl_q<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ n_fl_std+I(n_fl_std^2), data = .)) %>% tidy(model))
```

```r
seldiffs_nfl_q$sig<-ifelse(seldiffs_nfl_q$p.value<0.05,"*","")
kable(subset(seldiffs_nfl_q,term=="I(n_fl_std^2)"),digits=3)  #Quadratic selection differentials for nf
```

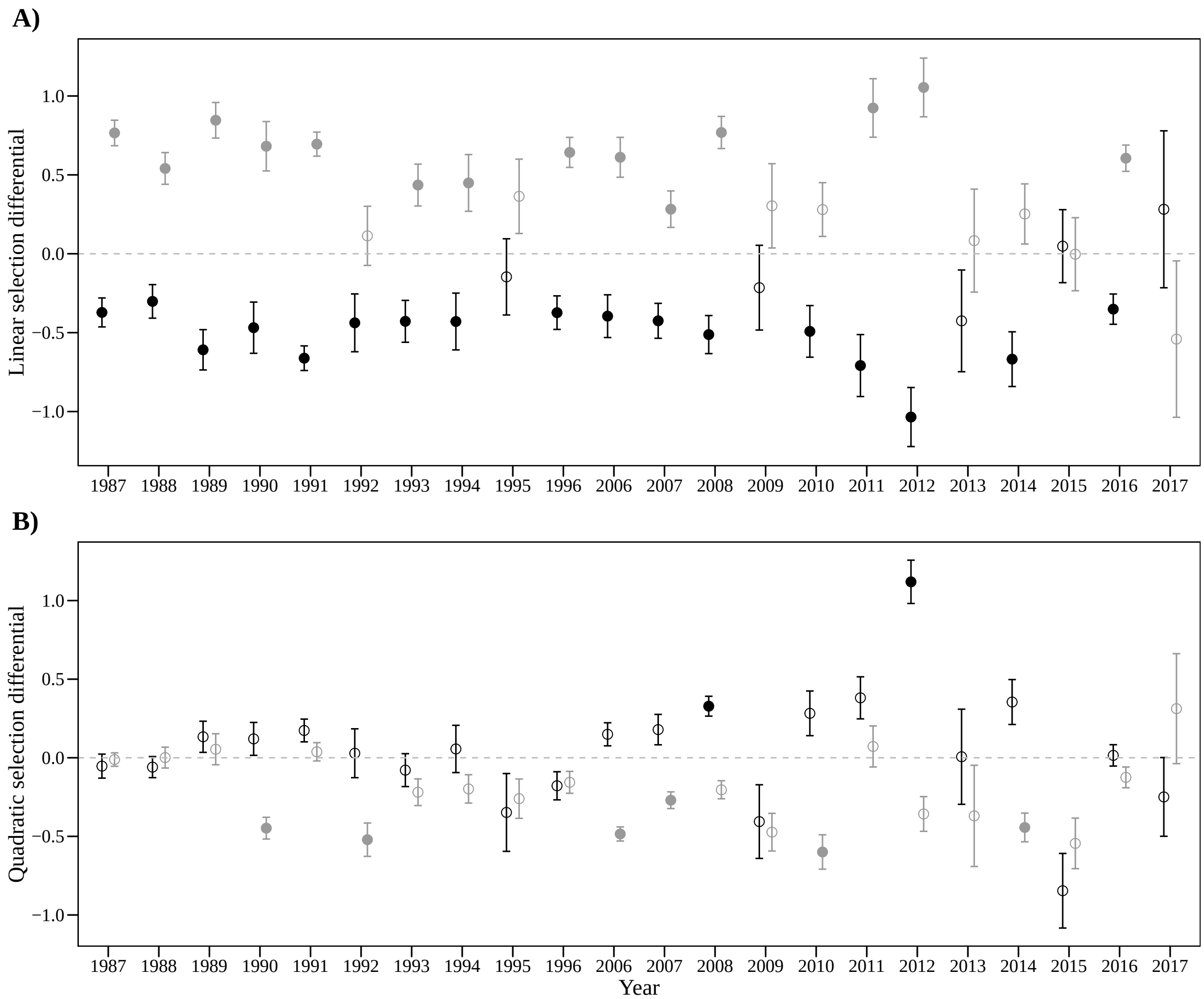
	year	term	estimate	std.error	statistic	p.value	sig
3	1987	I(n_fl_std^2)	-0.006	0.043	-0.135	0.892	
6	1988	I(n_fl_std^2)	0.001	0.066	0.009	0.993	
9	1989	I(n_fl_std^2)	0.027	0.099	0.274	0.785	
12	1990	I(n_fl_std^2)	-0.224	0.069	-3.234	0.002	*
15	1991	I(n_fl_std^2)	0.019	0.058	0.326	0.745	
18	1992	I(n_fl_std^2)	-0.261	0.106	-2.455	0.016	*
21	1993	I(n_fl_std^2)	-0.110	0.085	-1.293	0.198	
24	1994	I(n_fl_std^2)	-0.099	0.090	-1.098	0.274	
27	1995	I(n_fl_std^2)	-0.130	0.125	-1.039	0.305	
30	1996	I(n_fl_std^2)	-0.078	0.070	-1.121	0.264	
33	2006	I(n_fl_std^2)	-0.242	0.045	-5.402	0.000	*
36	2007	I(n_fl_std^2)	-0.135	0.053	-2.544	0.013	*
39	2008	I(n_fl_std^2)	-0.102	0.057	-1.775	0.080	
42	2009	I(n_fl_std^2)	-0.237	0.120	-1.976	0.053	
45	2010	I(n_fl_std^2)	-0.300	0.109	-2.740	0.008	*
48	2011	I(n_fl_std^2)	0.036	0.130	0.275	0.784	
51	2012	I(n_fl_std^2)	-0.179	0.110	-1.621	0.108	
54	2013	I(n_fl_std^2)	-0.185	0.322	-0.574	0.568	
57	2014	I(n_fl_std^2)	-0.222	0.091	-2.428	0.018	*
60	2015	I(n_fl_std^2)	-0.272	0.161	-1.694	0.100	
63	2016	I(n_fl_std^2)	-0.062	0.066	-0.944	0.347	
66	2017	I(n_fl_std^2)	0.156	0.350	0.447	0.656	

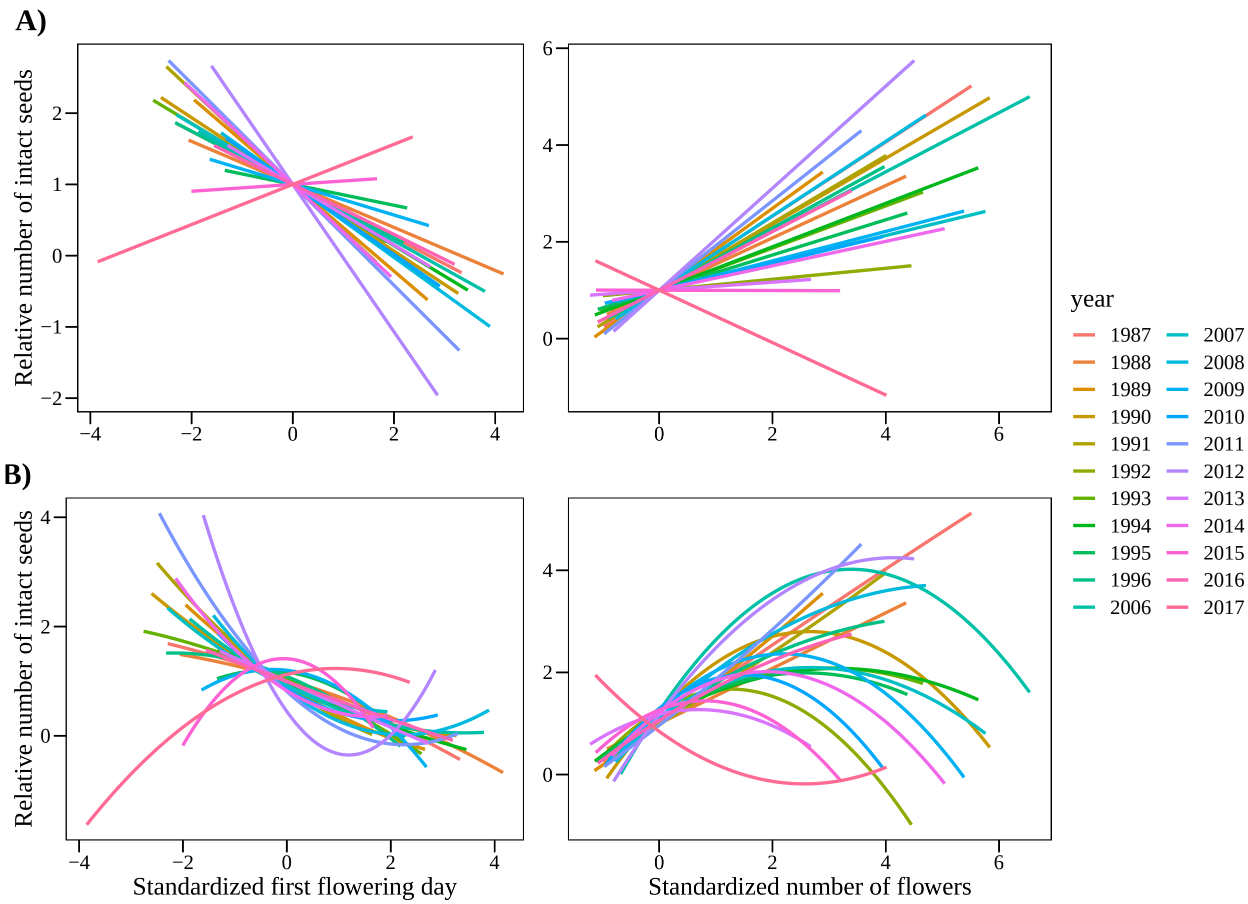
```r
#I(n_fl_std^2) * (stabilizing selection - decreases variance) in 1990,1992,2006,2007,2010,2014
```

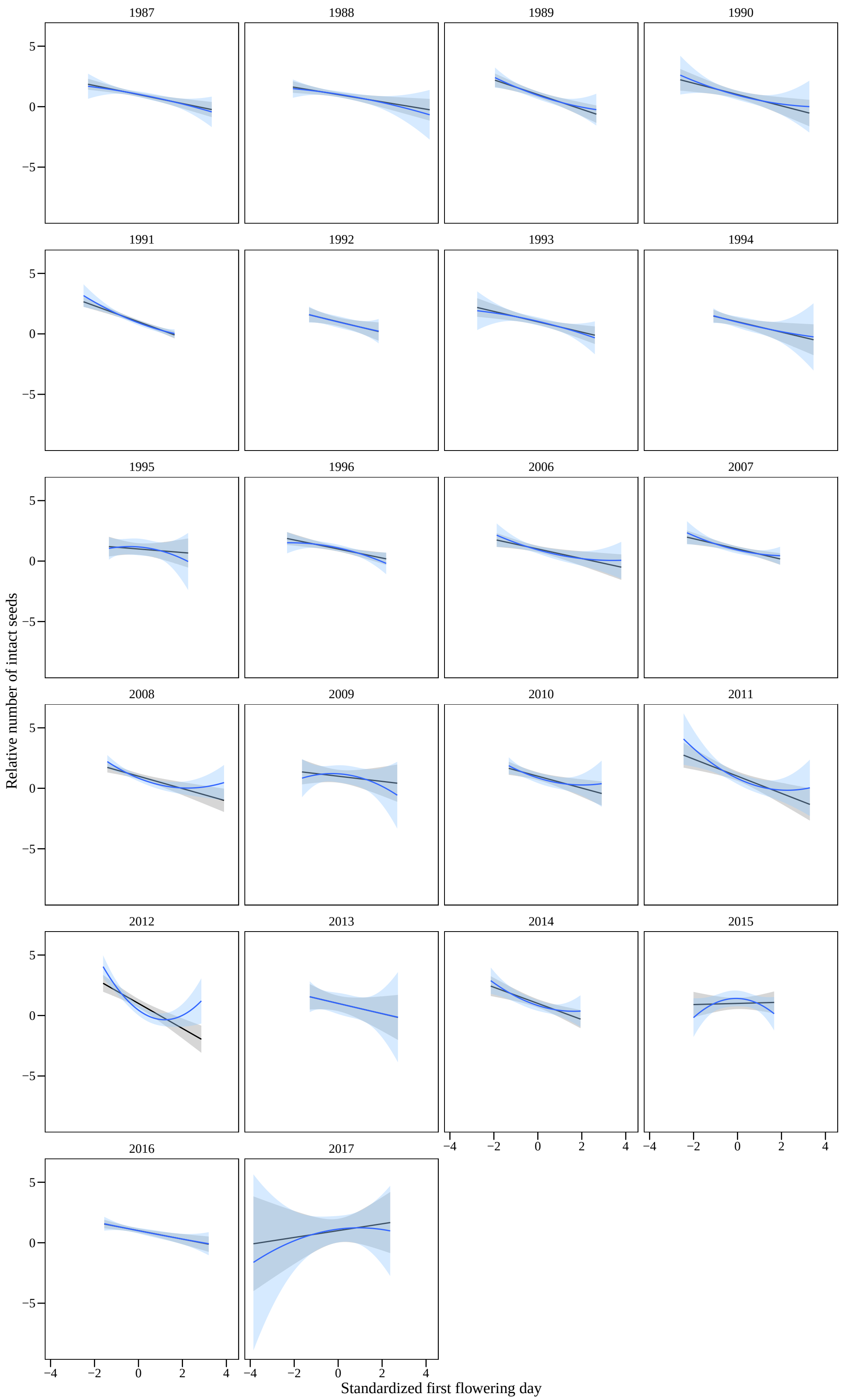
All selection differentials

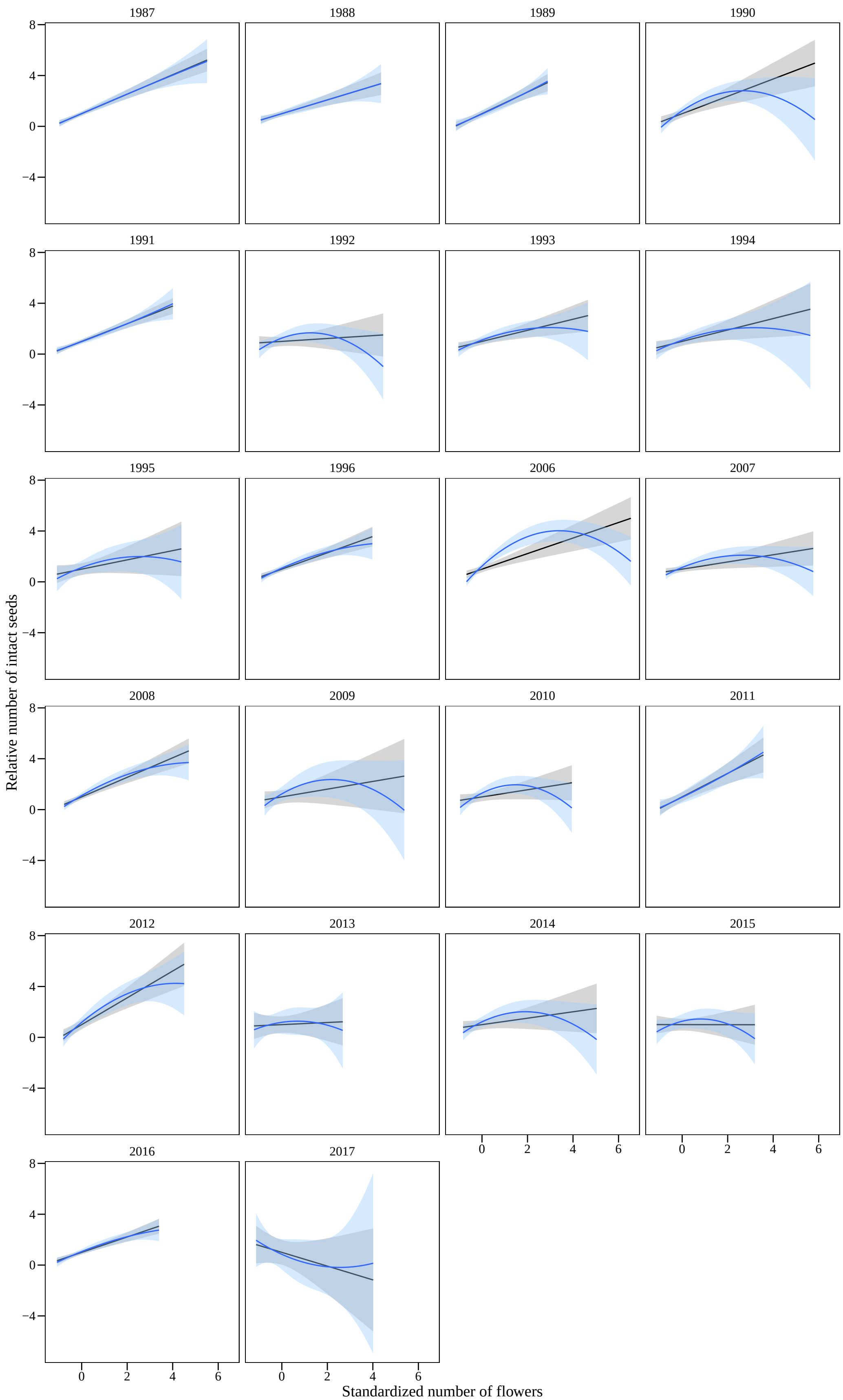
```r
seldiffs<-rbind(subset(seldiffs_FFD,term=="FFD_std")[c(1:4,7)],
                subset(seldiffs_FFD_q,term=="I(FFD_std^2)")[c(1:4,7)],
                subset(seldiffs_nfl,term=="n_fl_std")[c(1:4,7)],
                subset(seldiffs_nfl_q,term=="I(n_fl_std^2)")[c(1:4,7)])
```

Plots


A)
Linear selection differential
1.0
0.5
0.0
−0.5
−1.0
1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
B)
Quadratic selection differential
1.0
0.5
0.0
−0.5
−1.0
1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
Year


A)
B)
Relative number of intact seeds
Relative number of intact seeds
Standardized first flowering day
Standardized number of flowers
year
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Relative number of intact seeds
Standardized first flowering day
5
0
−5
−4
−2
0
2
4



1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
8
4
0
−4
0
2
4
6
Relative number of intact seeds
Standardized number of flowers

Selection gradients for each year

FFD, linear

```
selgrads_FFD<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std+n_fl_std, data = .)) %>% tidy(model))
selgrads_FFD$sig<-ifelse(selgrads_FFD$p.value<0.05,"*","")
kable(subset(selgrads_FFD,term=="FFD_std"),digits=3)  #Linear selection gradients for FFD
```

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	FFD_std	-0.078	0.088	-0.883	0.378	
5	1988	FFD_std	-0.088	0.111	-0.789	0.431	
8	1989	FFD_std	-0.144	0.143	-1.010	0.315	
11	1990	FFD_std	-0.240	0.169	-1.418	0.159	
14	1991	FFD_std	-0.398	0.087	-4.564	0.000	*
17	1992	FFD_std	-0.463	0.199	-2.323	0.022	*
20	1993	FFD_std	-0.300	0.144	-2.084	0.039	*
23	1994	FFD_std	-0.300	0.194	-1.545	0.124	
26	1995	FFD_std	0.018	0.266	0.069	0.945	
29	1996	FFD_std	-0.170	0.101	-1.684	0.095	
32	2006	FFD_std	-0.228	0.132	-1.733	0.086	
35	2007	FFD_std	-0.383	0.131	-2.922	0.004	*
38	2008	FFD_std	-0.210	0.112	-1.873	0.065	
41	2009	FFD_std	-0.070	0.321	-0.218	0.828	
44	2010	FFD_std	-0.478	0.195	-2.459	0.016	*
47	2011	FFD_std	-0.301	0.218	-1.379	0.172	
50	2012	FFD_std	-0.665	0.210	-3.174	0.002	*
53	2013	FFD_std	-0.426	0.331	-1.284	0.204	
56	2014	FFD_std	-0.777	0.211	-3.676	0.001	*
59	2015	FFD_std	0.083	0.315	0.264	0.794	
62	2016	FFD_std	-0.055	0.097	-0.563	0.575	
65	2017	FFD_std	-0.020	0.595	-0.034	0.973	

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

FFD, quadratic and correlational

```
selgrads_FFD_q<-data.frame(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
selgrads_FFD_q$sig<-ifelse(selgrads_FFD_q$p.value<0.05,"*","")
kable(subset(selgrads_FFD_q,term=="I(FFD_std^2)"),digits=3)
```

	year	term	estimate	std.error	statistic	p.value	sig
3	1987	I(FFD_std^2)	-0.071	0.085	-0.836	0.404	
9	1988	I(FFD_std^2)	0.091	0.075	1.208	0.229	
15	1989	I(FFD_std^2)	0.035	0.134	0.259	0.796	
21	1990	I(FFD_std^2)	-0.049	0.120	-0.410	0.682	
27	1991	I(FFD_std^2)	0.039	0.086	0.450	0.653	
33	1992	I(FFD_std^2)	0.096	0.184	0.525	0.600	

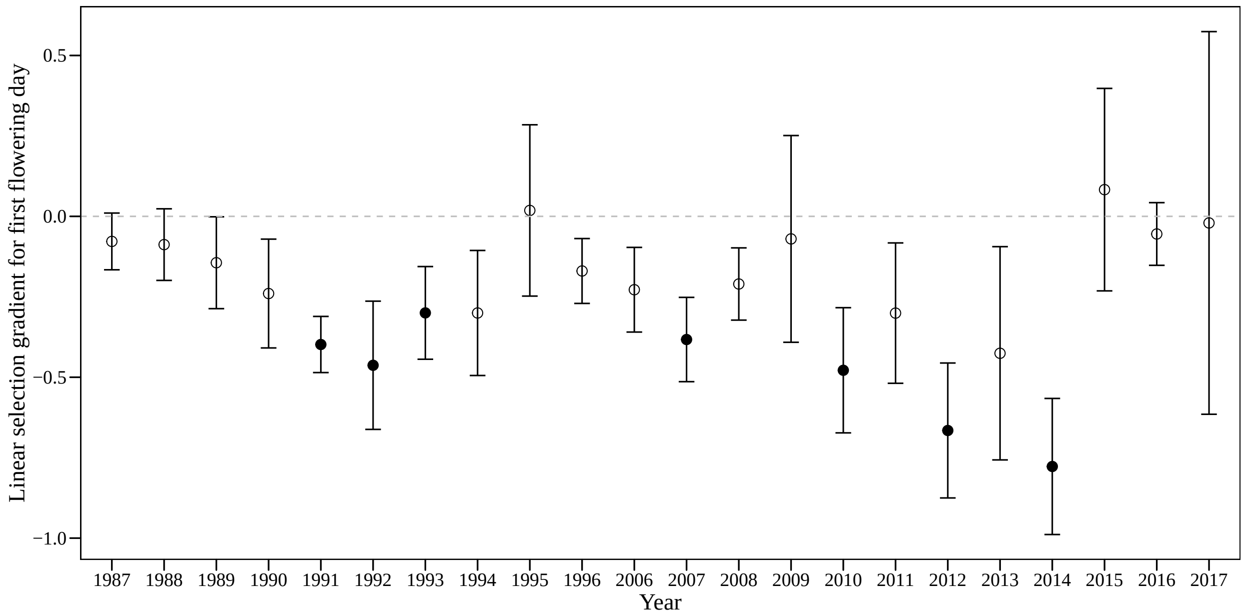
	year	term	estimate	std.error	statistic	p.value	sig
39	1993	I(FFD_std^2)	0.021	0.119	0.173	0.863	
45	1994	I(FFD_std^2)	-0.018	0.171	-0.104	0.917	
51	1995	I(FFD_std^2)	-0.229	0.308	-0.743	0.462	
57	1996	I(FFD_std^2)	-0.049	0.093	-0.529	0.598	
63	2006	I(FFD_std^2)	0.113	0.075	1.517	0.133	
69	2007	I(FFD_std^2)	0.243	0.150	1.626	0.108	
75	2008	I(FFD_std^2)	0.073	0.067	1.093	0.278	
81	2009	I(FFD_std^2)	-0.063	0.303	-0.207	0.837	
87	2010	I(FFD_std^2)	0.196	0.165	1.183	0.241	
93	2011	I(FFD_std^2)	0.052	0.171	0.302	0.763	
99	2012	I(FFD_std^2)	0.370	0.187	1.976	0.051	
105	2013	I(FFD_std^2)	0.178	0.362	0.491	0.625	
111	2014	I(FFD_std^2)	0.340	0.207	1.645	0.105	
117	2015	I(FFD_std^2)	-0.975	0.364	-2.679	0.012	*
123	2016	I(FFD_std^2)	0.005	0.076	0.062	0.951	
129	2017	I(FFD_std^2)	-0.206	0.406	-0.507	0.613	

```
#Quadratic selection gradients for FFD
#I(FFD_std^2) * (stabilizing selection - decreases variance) in 2015
kable(subset(selgrads_FFD_q,term=="FFD_std:n_fl_std"),digits=3)
```

	year	term	estimate	std.error	statistic	p.value	sig
6	1987	FFD_std:n_fl_std	0.010	0.180	0.058	0.954	
12	1988	FFD_std:n_fl_std	0.578	0.179	3.236	0.001	*
18	1989	FFD_std:n_fl_std	0.061	0.225	0.271	0.787	
24	1990	FFD_std:n_fl_std	-0.352	0.278	-1.264	0.209	
30	1991	FFD_std:n_fl_std	0.122	0.165	0.742	0.459	
36	1992	FFD_std:n_fl_std	0.172	0.252	0.681	0.497	
42	1993	FFD_std:n_fl_std	0.153	0.194	0.787	0.432	
48	1994	FFD_std:n_fl_std	-0.081	0.236	-0.344	0.731	
54	1995	FFD_std:n_fl_std	-0.154	0.443	-0.347	0.730	
60	1996	FFD_std:n_fl_std	-0.006	0.139	-0.041	0.967	
66	2006	FFD_std:n_fl_std	0.360	0.210	1.713	0.090	
72	2007	FFD_std:n_fl_std	0.394	0.266	1.481	0.142	
78	2008	FFD_std:n_fl_std	-0.096	0.246	-0.393	0.696	
84	2009	FFD_std:n_fl_std	1.285	0.794	1.619	0.111	
90	2010	FFD_std:n_fl_std	0.379	0.358	1.061	0.293	
96	2011	FFD_std:n_fl_std	-0.318	0.507	-0.629	0.531	
102	2012	FFD_std:n_fl_std	-0.335	0.430	-0.778	0.438	
108	2013	FFD_std:n_fl_std	0.455	0.449	1.013	0.315	
114	2014	FFD_std:n_fl_std	0.315	0.351	0.896	0.374	
120	2015	FFD_std:n_fl_std	-1.041	0.555	-1.875	0.071	
126	2016	FFD_std:n_fl_std	0.500	0.189	2.640	0.010	*
132	2017	FFD_std:n_fl_std	-0.006	0.759	-0.008	0.994	

```
#Correlational selection gradients
#FFD_std:n_fl_std* (correlational selection) in 1988 and 2016
```

Plots



Calculate BCa confindence intervals for model estimates? (selection differentials and gradients)

Fig. 1: Among-year variation

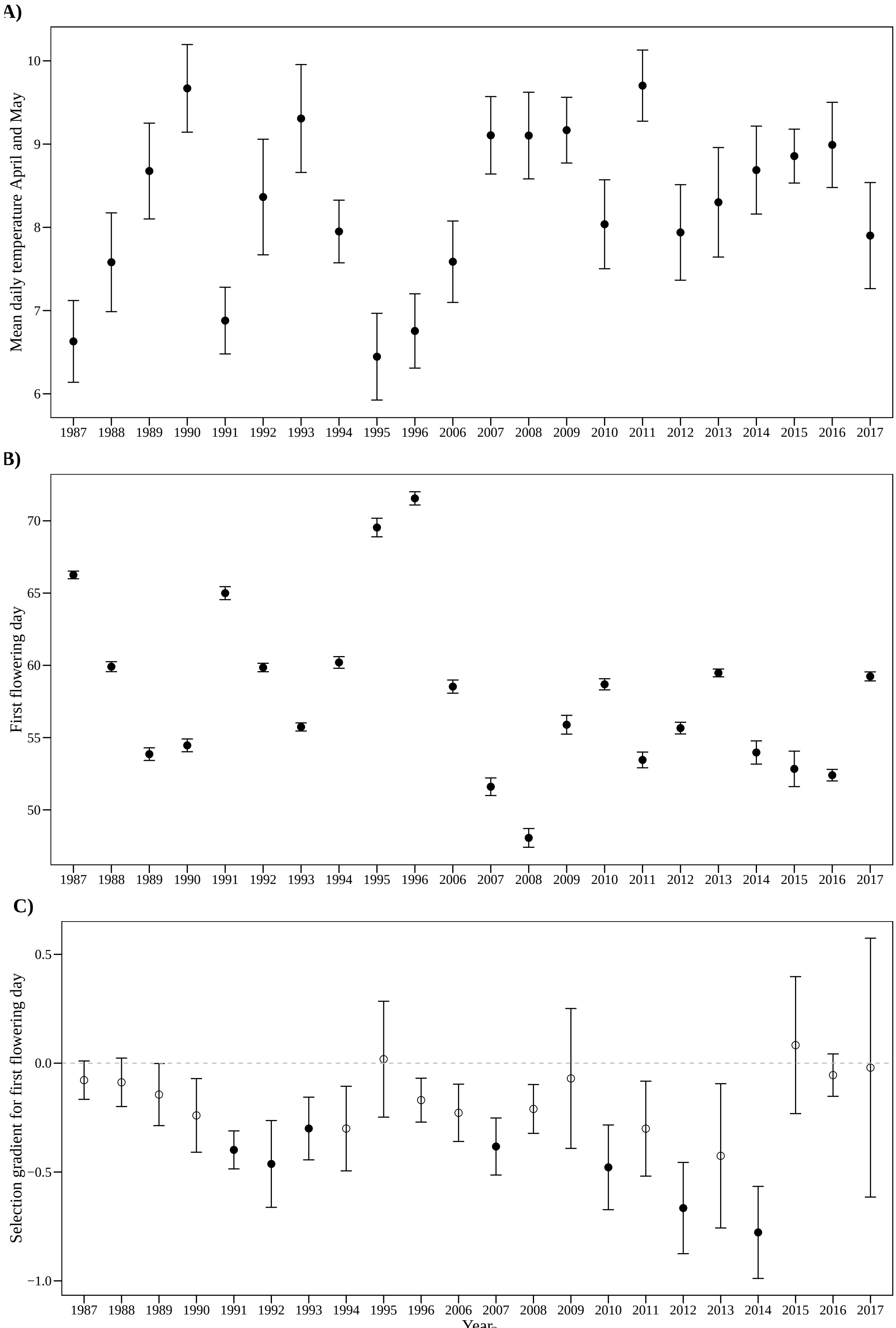


Fig. 2: Response of FFD to spring temperature

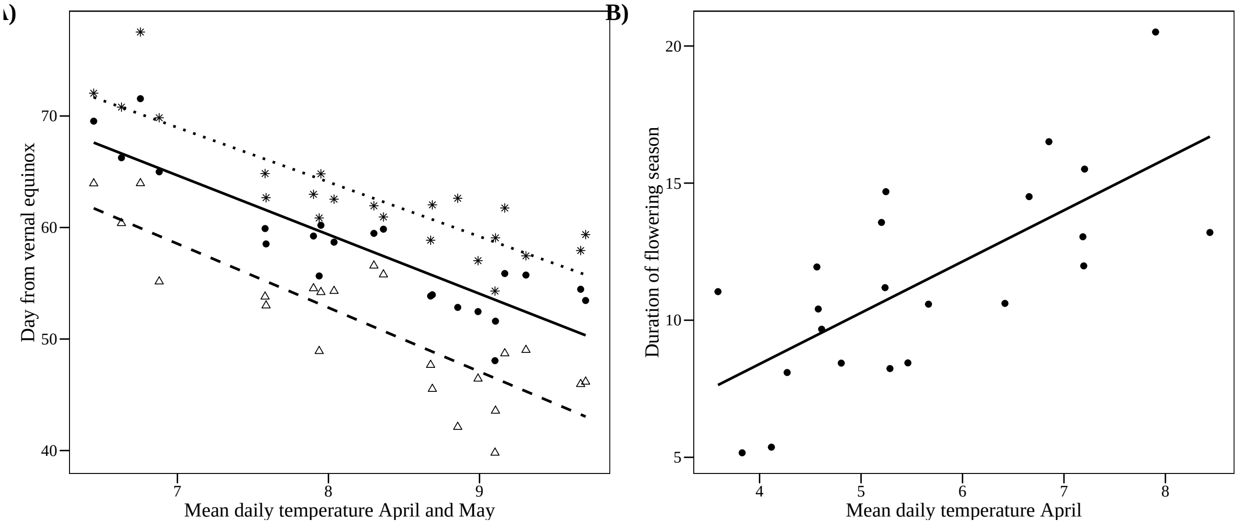
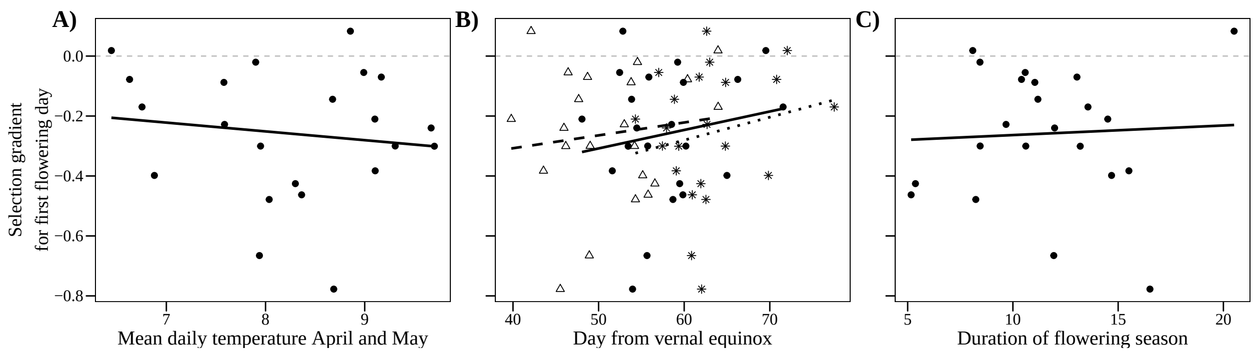


Fig. 3: Response of selection gradients to spring temperature, position and duration of flowering season



Results 1: Response of position and duration of flowering to temperature

Position

```
tidy(lm(FFD_mean~mean_45,data=mean_weather8))
```

```
##          term   estimate std.error statistic      p.value
## 1 (Intercept) 101.819401 5.3039561  19.19688 2.358163e-14
## 2     mean_45  -5.306504 0.6381746  -8.31513 6.384486e-08
```

```
glance(lm(FFD_mean~mean_45,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] 0.7644192
```

```r
predict(lm(FFD_mean~mean_45,data=mean_weather8),
        data.frame(mean_45=with(mean_weather8,min(mean_45)))) # Coldest
```

```
##       1
## 67.6142
```

```r
predict(lm(FFD_mean~mean_45,data=mean_weather8),
        data.frame(mean_45=with(mean_weather8,max(mean_45)))) # Warmest
```

```
##        1
## 50.33326
```

```r
tidy(lm(date_10~mean_45,data=mean_weather8))
```

```
##          term  estimate std.error statistic      p.value
## 1 (Intercept) 98.698162 6.7044762 14.721234 3.399455e-12
## 2     mean_45 -5.735923 0.8066858 -7.110479 6.849247e-07
```

```r
glance(lm(date_10~mean_45,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] 0.7023764
```

```r
predict(lm(date_10~mean_45,data=mean_weather8),
        data.frame(mean_45=with(mean_weather8,min(mean_45)))) # Coldest
```

```
##        1
## 61.72497
```

```r
predict(lm(date_10~mean_45,data=mean_weather8),
        data.frame(mean_45=with(mean_weather8,max(mean_45)))) # Warmest
```

```
##        1
## 43.04561
```

```r
tidy(lm(date_90~mean_45,data=mean_weather8))
```

```
##          term   estimate std.error statistic      p.value
## 1 (Intercept) 103.191933 5.1266511 20.128527 9.556363e-15
## 2     mean_45  -4.888898 0.6168412 -7.925701 1.346007e-07
```

```r
glance(lm(date_90~mean_45,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] 0.7464281
```

```r
predict(lm(date_90~mean_45,data=mean_weather8),
        data.frame(mean_45=with(mean_weather8,min(mean_45)))) # Coldest
```

```
##        1
## 71.67857
```

```r
predict(lm(date_90~mean_45,data=mean_weather8),
        data.frame(mean_45=with(mean_weather8,max(mean_45)))) # Warmest
```

```
##       1
## 55.7576
```

Duration

```r
tidy(lm(days_90_10~mean_4,data=mean_weather8))
```

```
##          term  estimate std.error statistic      p.value
## 1 (Intercept) 0.9283669 2.4224101  0.383241 0.7055842867
## 2      mean_4 1.8685295 0.4170708  4.480125 0.0002291409
```

```r
glance(lm(days_90_10~mean_4,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] 0.475937
```

```r
predict(lm(days_90_10~mean_4,data=mean_weather8),
        data.frame(mean_4=with(mean_weather8,min(mean_4)))) # Coldest
```

```
##        1
## 7.636388
```

```r
predict(lm(days_90_10~mean_4,data=mean_weather8),
        data.frame(mean_4=with(mean_weather8,max(mean_4)))) # Warmest
```

```
##        1
## 16.69564
```

Results 2: Differences in selection among years

Indirect selection (selection differentials)

```r
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
```

```r
#Indirect selection for early flowering differs among years
```

Direct selection (selection gradients)

```r
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
```

```r
#Direct selection for early flowering differs among years
```

Results 3: Are differences in selection among years related to climatic conditions?

Response of selection to spring temperature, position and duration of flowering season.

Selection gradients

Spring temperature

```r
tidy(lm(selgrad_FFD~mean_45,data=mean_weather8))
```

```
##          term    estimate  std.error   statistic   p.value
## 1 (Intercept) -0.01691068 0.41242897 -0.04100265 0.9677003
## 2     mean_45 -0.02929631 0.04962365 -0.59036988 0.5615549
```

```r
glance(lm(selgrad_FFD~mean_45,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.03201525
```

Position of the flowering season

```r
tidy(lm(selgrad_FFD~date_10,data=mean_weather8))
```

```
##          term    estimate   std.error  statistic   p.value
## 1 (Intercept) -0.47914684 0.379020823 -1.2641702 0.2207042
## 2     date_10  0.00429208 0.007324249  0.5860096 0.5644245
```

```r
glance(lm(selgrad_FFD~date_10,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.03227546
```

```r
tidy(lm(selgrad_FFD~FFD_mean,data=mean_weather8))
```

```
##          term     estimate   std.error  statistic   p.value
## 1 (Intercept) -0.616165373 0.477559366 -1.2902383 0.2116866
## 2    FFD_mean  0.006160856 0.008192303  0.7520298 0.4607926
```

```r
glance(lm(selgrad_FFD~FFD_mean,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.02112519
```

```r
tidy(lm(selgrad_FFD~date_90,data=mean_weather8))
```

```
##          term     estimate   std.error  statistic   p.value
## 1 (Intercept) -0.739462930 0.551824694 -1.3400323 0.1952617
## 2     date_90  0.007650619 0.008751133  0.8742433 0.3923630
```

```r
glance(lm(selgrad_FFD~date_90,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.01135115
```

Duration of the flowering season

```
tidy(lm(selgrad_FFD~days_90_10,data=mean_weather8))
```

```
##          term    estimate  std.error statistic    p.value
## 1 (Intercept) -0.29547089 0.16188624 -1.825176 0.08294729
## 2  days_90_10  0.00319399 0.01346601  0.237189 0.81492285
```

```
glance(lm(selgrad_FFD~days_90_10,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.04705471
```

Selection differentials

```
mean_weather8<-merge(mean_weather8,subset(seldiffs_FFD,term=="FFD_std")[c(1,3)])
names(mean_weather8)[242]<-"seldiff_FFD"
```

Spring temperature

```
tidy(lm(seldiff_FFD~mean_45,data=mean_weather8))
```

```
##          term    estimate  std.error  statistic   p.value
## 1 (Intercept) -0.13157965 0.50133952 -0.2624562 0.7956542
## 2     mean_45 -0.03430635 0.06032142 -0.5687259 0.5758735
```

```
glance(lm(seldiff_FFD~mean_45,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.03328917
```

Position of the flowering season

```
tidy(lm(seldiff_FFD~date_10,data=mean_weather8))
```

```
##          term     estimate   std.error  statistic    p.value
## 1 (Intercept) -0.809507737 0.455781837 -1.7760860 0.09093614
## 2     date_10  0.007687512 0.008807589  0.8728281 0.39311566
```

```
glance(lm(seldiff_FFD~date_10,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.01147158
```

```
tidy(lm(seldiff_FFD~FFD_mean,data=mean_weather8))
```

```
##          term     estimate   std.error  statistic   p.value
## 1 (Intercept) -0.886000203 0.578692036 -1.5310392 0.1414246
## 2    FFD_mean  0.008122678 0.009927186  0.8182257 0.4228704
```

```
glance(lm(seldiff_FFD~FFD_mean,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.01599007
```

```
tidy(lm(seldiff_FFD~date_90,data=mean_weather8))
```

```
##          term     estimate  std.error  statistic   p.value
## 1 (Intercept) -0.990628717 0.67072636 -1.4769491 0.1552631
## 2     date_90  0.009164788 0.01063674  0.8616163 0.3991116
```

```
glance(lm(seldiff_FFD~date_90,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.01241985
```

Duration of the flowering season

```
tidy(lm(seldiff_FFD~days_90_10,data=mean_weather8))
```

```
##          term     estimate  std.error statistic   p.value
## 1 (Intercept) -0.361303201 0.19654186 -1.838302 0.0809177
## 2  days_90_10 -0.004658457 0.01634873 -0.284943 0.7786175
```

```
glance(lm(seldiff_FFD~days_90_10,data=mean_weather8))$adj.r.squared # Rsquare
```

```
## [1] -0.04575463
```

Mixed models

```
data_sel<-merge(data_sel,mean_weather8[c(1,158,218,236,239,240)])
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:mean_45+n_fl_std+(1|year),data = data_sel),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel
##                   Chisq Df Pr(>Chisq)
## FFD_std         29.9759  1  4.375e-08 ***
## n_fl_std        72.2770  1  < 2.2e-16 ***
## FFD_std:mean_45  0.1552  1     0.6936
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#No influences of spring temperature on selection on FFD
```

```
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:date_10+n_fl_std+(1|year),data = data_sel),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel
##                  Chisq Df Pr(>Chisq)
## FFD_std         29.986  1  4.352e-08 ***
## n_fl_std        71.521  1  < 2.2e-16 ***
## FFD_std:date_10  0.984  1     0.3212
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#No influences of date_10 on selection on FFD
```

```
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:FFD_mean+n_fl_std+(1|year),data = data_sel),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
```

```
## Response: n_intact_seeds_rel
##                     Chisq Df Pr(>Chisq)
## FFD_std           29.9784  1  4.369e-08 ***
## n_fl_std          71.9743  1  < 2.2e-16 ***
## FFD_std:FFD_mean   0.3614  1     0.5477
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#No influences of FFD_mean on selection on FFD
```

```
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:date_90+n_fl_std+(1|year),data = data_sel),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel
##                    Chisq Df Pr(>Chisq)
## FFD_std          29.9772  1  4.372e-08 ***
## n_fl_std         72.2185  1  < 2.2e-16 ***
## FFD_std:date_90   0.2619  1     0.6088
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#No influences of date_90 on selection on FFD
```

```
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:days_90_10+n_fl_std+(1|year),data = data_sel),type="II"
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel
##                      Chisq Df Pr(>Chisq)
## FFD_std             29.987  1  4.349e-08 ***
## n_fl_std            71.278  1  < 2.2e-16 ***
## FFD_std:days_90_10  1.096  1     0.2951
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#No influences of days_90_10 on selection on FFD
```