# Results Lathyrus paper 1

## Contents

## Select data and look at variables

```r
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
```

```r
data_sel_agg$year<-as.factor(data_sel_agg$year)
data_sel<-merge(data_sel[c(1:19,56)],data_sel_agg[c(1:217,223:235)],by="year")
```

## Calculation of relative fitness and standardized traits

Relativization and standardization was done within each year.

```r
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

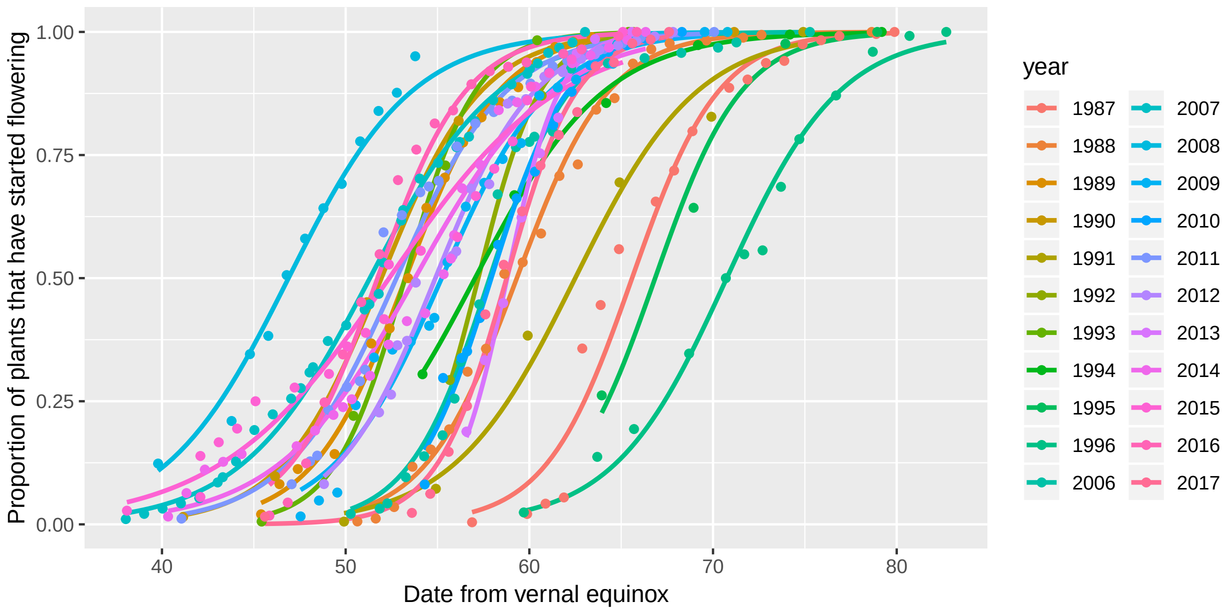
```r
propfl<-as.data.frame(aggregate(id~FFD+year,data=alldata_weather_subs[c(1:2,4)],FUN=length) %>%
        group_by(year) %>%
        mutate(n_cum_FFD = cumsum(x = id))) #Cumulated n plants fl per yr at each FFD

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

```r
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)  %>%
```

```r
           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
```

```r
mean_weather7<-merge(mean_weather6,fl_pos_dur[c(1,3:4,9:13)])
data_sel<-merge(data_sel,fl_pos_dur)
```

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

### With FFD_first

```r
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 |

| variable | Estimate | P | sig | Rsquare |
|---|---|---|---|---|
| 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 |
| 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 |

| variable | Estimate | P | sig | Rsquare |
|---|---|---|---|---|
| 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 |
| 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 |

| variable | Estimate | P | sig | Rsquare |
|---|---|---|---|---|
| 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 |
| 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

```r
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 |

## With FFD_mean

```
models21<-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_mean ~ scale(i), list(i = as.name(x))),
                          data = mean_weather7)})
models21_summary<-lapply(X = models21, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models21_summary<-models21_summary[c(1:2,5,6)]
names(models21_summary)<-c("variable","Estimate","P","sig")
models21_summary<-subset(models21_summary,!variable=="(Intercept)")
models21_summary<-cbind(models21_summary,sapply(lapply(X = models21, FUN = summary), "[[", 9))
names(models21_summary)[5]<-"Rsquare"
kable(arrange(subset(models21_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

| variable | Estimate | P | sig | Rsquare |
|---|---|---|---|---|
| scale(mean_45) | -5.189354 | <0.001 | *** | 0.7644192 |
| scale(GDD3_45) | -5.044179 | <0.001 | *** | 0.7194888 |
| scale(GDH3_45) | -5.017876 | <0.001 | *** | 0.7114849 |
| scale(max_45) | -4.966059 | <0.001 | *** | 0.6958392 |
| scale(GDH5_45) | -4.880152 | <0.001 | *** | 0.6702579 |
| scale(min_45) | -4.867603 | <0.001 | *** | 0.6665584 |
| scale(GDD5_45) | -4.812688 | <0.001 | *** | 0.6504817 |
| scale(GDD3_16) | -4.635369 | <0.001 | *** | 0.5998155 |
| scale(max_46) | -4.632479 | <0.001 | *** | 0.5990053 |
| scale(mean_b) | -4.595254 | <0.001 | *** | 0.5886171 |
| scale(mean_46) | -4.592294 | <0.001 | *** | 0.5877946 |
| scale(GDH3_16) | -4.587069 | <0.001 | *** | 0.5863439 |
| scale(GDH7_45) | -4.582832 | <0.001 | *** | 0.5851690 |
| scale(GDD3_b) | -4.579945 | <0.001 | *** | 0.5843690 |
| scale(GDH3_b) | -4.545754 | <0.001 | *** | 0.5749327 |
| scale(max_b) | -4.503158 | <0.001 | *** | 0.5632756 |
| scale(GDH5_b) | -4.411765 | <0.001 | *** | 0.5386352 |
| scale(GDD3_46) | -4.408219 | <0.001 | *** | 0.5376892 |
| scale(GDD7_45) | -4.382465 | <0.001 | *** | 0.5308423 |
| scale(GDH5_16) | -4.357646 | <0.001 | *** | 0.5242821 |
| scale(GDH3_46) | -4.347540 | <0.001 | *** | 0.5216214 |
| scale(GDD5_b) | -4.289443 | <0.001 | *** | 0.5064463 |

| variable | Estimate | P | sig | Rsquare |
|---|---|---|---|---|
| scale(GDD5_16) | -4.264398 | <0.001 | *** | 0.4999672 |
| scale(max_16) | -4.212815 | <0.001 | *** | 0.4867426 |
| scale(GDH7_b) | -4.123679 | <0.001 | *** | 0.4642699 |
| scale(GDD5_46) | -4.106000 | <0.001 | *** | 0.4598697 |
| scale(GDH5_46) | -4.099952 | <0.001 | *** | 0.4583689 |
| scale(GDH10_45) | -3.925744 | 0.001 | *** | 0.4160853 |
| scale(min_46) | -3.910445 | 0.001 | *** | 0.4124596 |
| scale(GDH7_16) | -3.906964 | 0.001 | *** | 0.4116365 |
| scale(mean_5) | -3.900101 | 0.001 | *** | 0.4100162 |
| scale(max_5) | -3.856773 | 0.001 | *** | 0.3998518 |
| scale(GDD3_5) | -3.850707 | 0.001 | *** | 0.3984379 |
| scale(mean_16) | -3.843845 | 0.001 | ** | 0.3968412 |
| scale(GDH3_5) | -3.826077 | 0.001 | ** | 0.3927197 |
| scale(GDD5_5) | -3.816282 | 0.001 | ** | 0.3904556 |
| scale(GDH5_5) | -3.759896 | 0.001 | ** | 0.3775364 |
| scale(GDD3_34) | -3.759883 | 0.001 | ** | 0.3775333 |
| scale(GDD7_b) | -3.757060 | 0.001 | ** | 0.3768917 |
| scale(GDH7_46) | -3.720840 | 0.002 | ** | 0.3687005 |
| scale(GDD7_16) | -3.697863 | 0.002 | ** | 0.3635453 |
| scale(GDH3_34) | -3.668764 | 0.002 | ** | 0.3570624 |
| scale(min_b) | -3.662870 | 0.002 | ** | 0.3557554 |
| scale(GDD7_5) | -3.627302 | 0.002 | ** | 0.3479135 |
| scale(GDD7_46) | -3.615971 | 0.002 | ** | 0.3454315 |
| scale(GDH7_5) | -3.607169 | 0.002 | ** | 0.3435086 |
| scale(min_5) | -3.562855 | 0.003 | ** | 0.3338996 |
| scale(max_34) | -3.553435 | 0.003 | ** | 0.3318722 |
| scale(GDH5_34) | -3.408210 | 0.005 | ** | 0.3012967 |
| scale(GDH10_b) | -3.373028 | 0.005 | ** | 0.2940815 |
| scale(mean_34) | -3.360440 | 0.006 | ** | 0.2915180 |
| scale(min_4) | -3.350947 | 0.006 | ** | 0.2895912 |
| scale(mean_4) | -3.346046 | 0.006 | ** | 0.2885986 |
| scale(min_16) | -3.339803 | 0.006 | ** | 0.2873363 |
| scale(GDD10_45) | -3.281799 | 0.007 | ** | 0.2757207 |
| scale(GDH10_5) | -3.264463 | 0.007 | ** | 0.2722885 |
| scale(GDD5_34) | -3.260892 | 0.008 | ** | 0.2715839 |
| scale(GDD3_4) | -3.179679 | 0.01 | ** | 0.2557651 |
| scale(GDH10_16) | -3.177653 | 0.01 | ** | 0.2553757 |
| scale(GDD3_13) | -3.130368 | 0.011 | * | 0.2463550 |
| scale(GDH3_13) | -3.117478 | 0.011 | * | 0.2439194 |
| scale(GDH10_46) | -3.103625 | 0.012 | * | 0.2413129 |
| scale(GDH7_34) | -3.101454 | 0.012 | * | 0.2409056 |
| scale(GDH3_4) | -3.073732 | 0.013 | * | 0.2357284 |
| scale(max_13) | -3.071511 | 0.013 | * | 0.2353156 |
| scale(max_3) | -2.980283 | 0.016 | * | 0.2186187 |
| scale(mean_13) | -2.961587 | 0.017 | * | 0.2152592 |
| scale(GDD10_5) | -2.946252 | 0.018 | * | 0.2125193 |
| scale(GDD3_3) | -2.921262 | 0.019 | * | 0.2080848 |
| scale(GDH3_3) | -2.915207 | 0.019 | * | 0.2070160 |
| scale(GDH5_4) | -2.900750 | 0.02 | * | 0.2044732 |
| scale(GDD5_4) | -2.876729 | 0.021 | * | 0.2002760 |
| scale(max_4) | -2.857728 | 0.022 | * | 0.1969808 |
| scale(GDH5_13) | -2.832867 | 0.024 | * | 0.1927021 |

| variable | Estimate | P | sig | Rsquare |
|---|---|---|---|---|
| scale(min__34) | -2.813026 | 0.025 | * | 0.1893145 |
| scale(min__13) | -2.798831 | 0.025 | * | 0.1869053 |
| scale(GDD10__16) | -2.739030 | 0.029 | * | 0.1768897 |
| scale(GDD10__46) | -2.721254 | 0.03 | * | 0.1739544 |
| scale(precipitation__13) | -2.712312 | 0.031 | * | 0.1724851 |
| scale(GDH7__4) | -2.703993 | 0.032 | * | 0.1711223 |
| scale(GDD7__34) | -2.690342 | 0.033 | * | 0.1688953 |
| scale(mean__3) | -2.657436 | 0.035 | * | 0.1635733 |
| scale(GDH5__3) | -2.656617 | 0.035 | * | 0.1634417 |
| scale(GDH10__34) | -2.503700 | 0.049 | * | 0.1395771 |

## 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 | * |

| | year | term | estimate | std.error | statistic | p.value | sig |
|---|---|---|---|---|---|---|---|
| 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 | |
| 51 | 2012 | I(FFD_std^2) | 0.560 | 0.138 | 4.063 | 0.000 | * |

| | year | term | estimate | std.error | statistic | p.value | sig |
|---|---|---|---|---|---|---|---|
| 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))
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
```

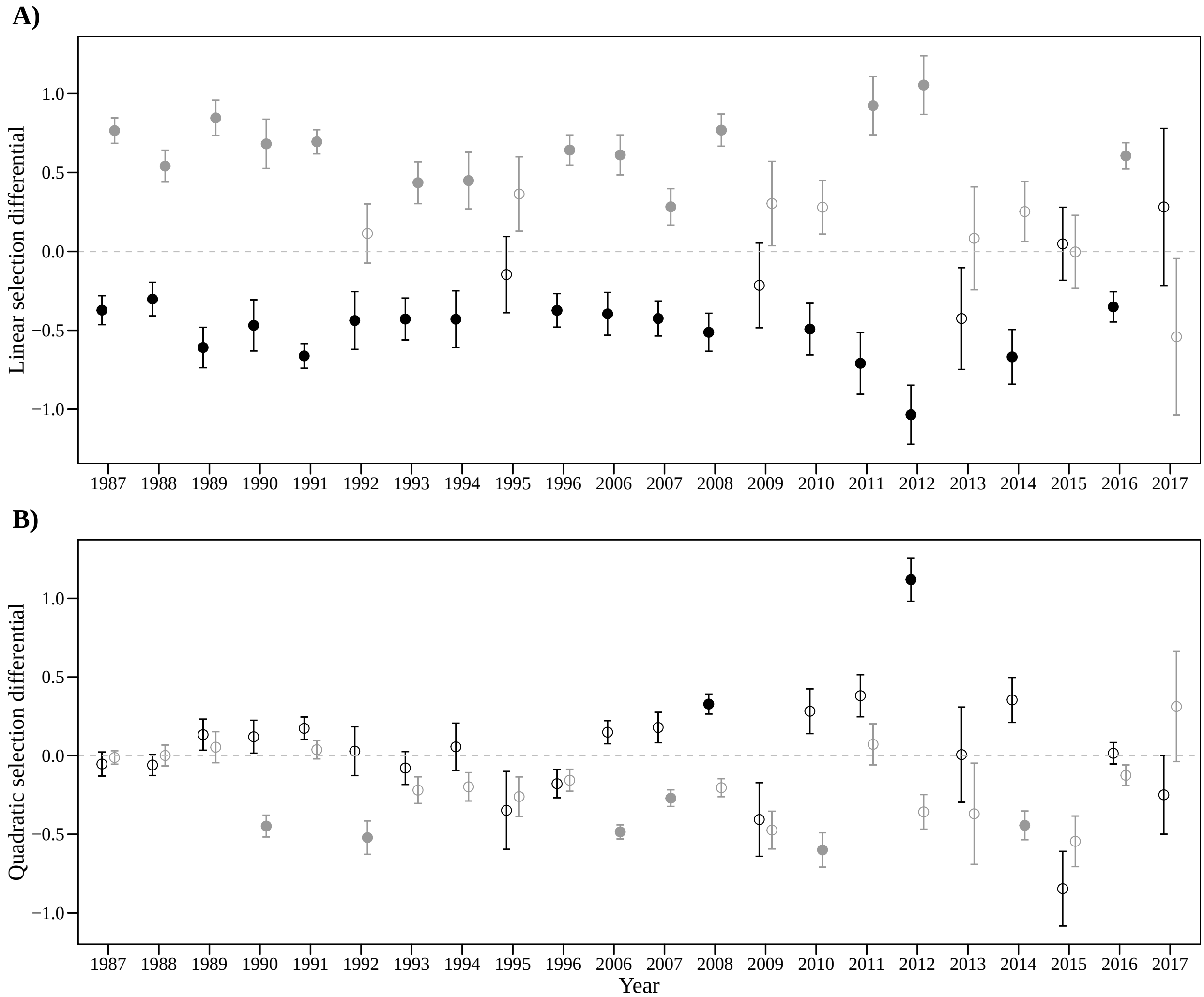
| | year | term | estimate | std.error | statistic | p.value | sig |
|---|---|---|---|---|---|---|---|
| 3 | 1987 | I(n_fl_std^2) | -0.006 | 0.043 | -0.135 | 0.892 | |
| 6 | 1988 | I(n_fl_std^2) | 0.001 | 0.066 | 0.009 | 0.993 | |
| 9 | 1989 | I(n_fl_std^2) | 0.027 | 0.099 | 0.274 | 0.785 | |
| 12 | 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 | |

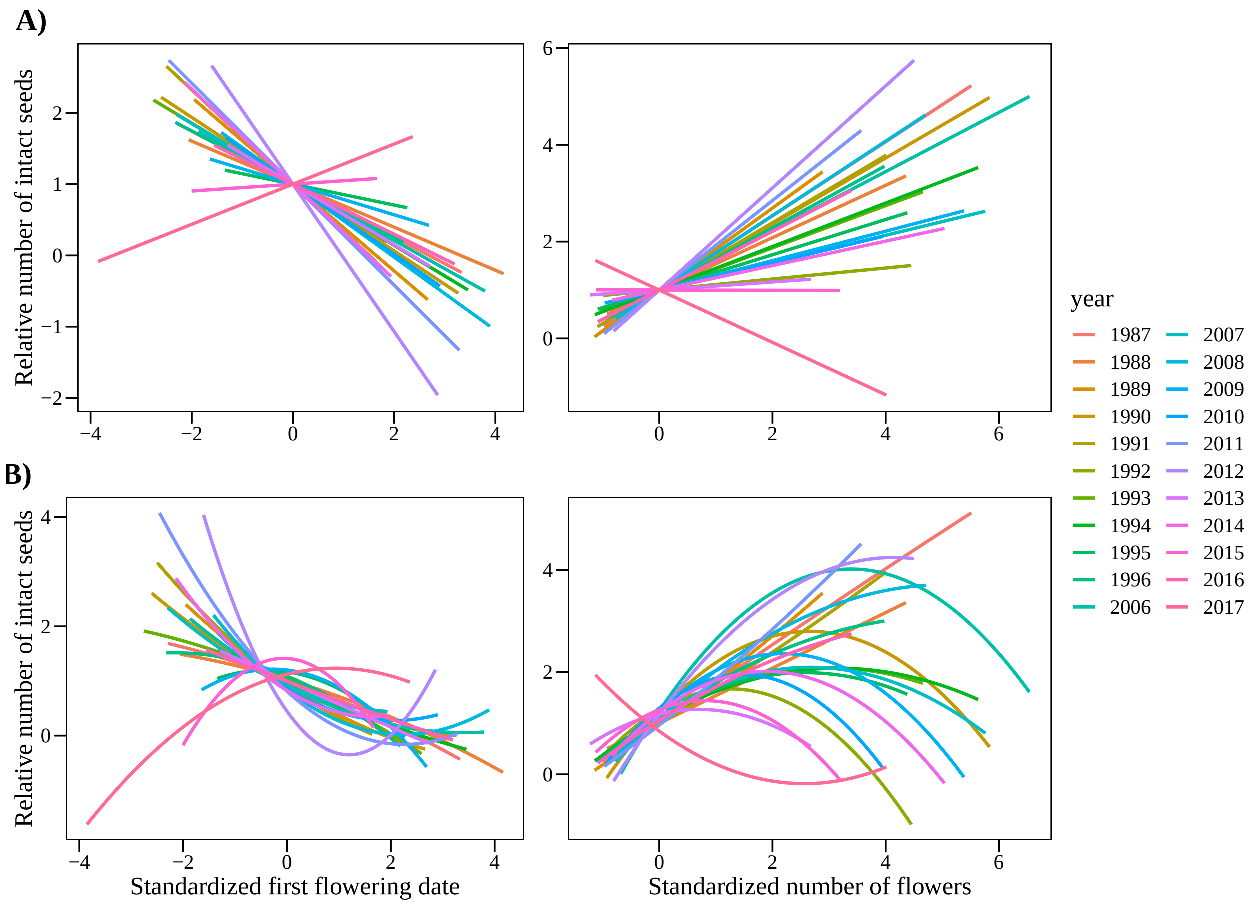
```
#I(n_fl_std^2) * (stabilizing selection - decreases variance) in 1990,1992,2006,2007,2010,2014
```

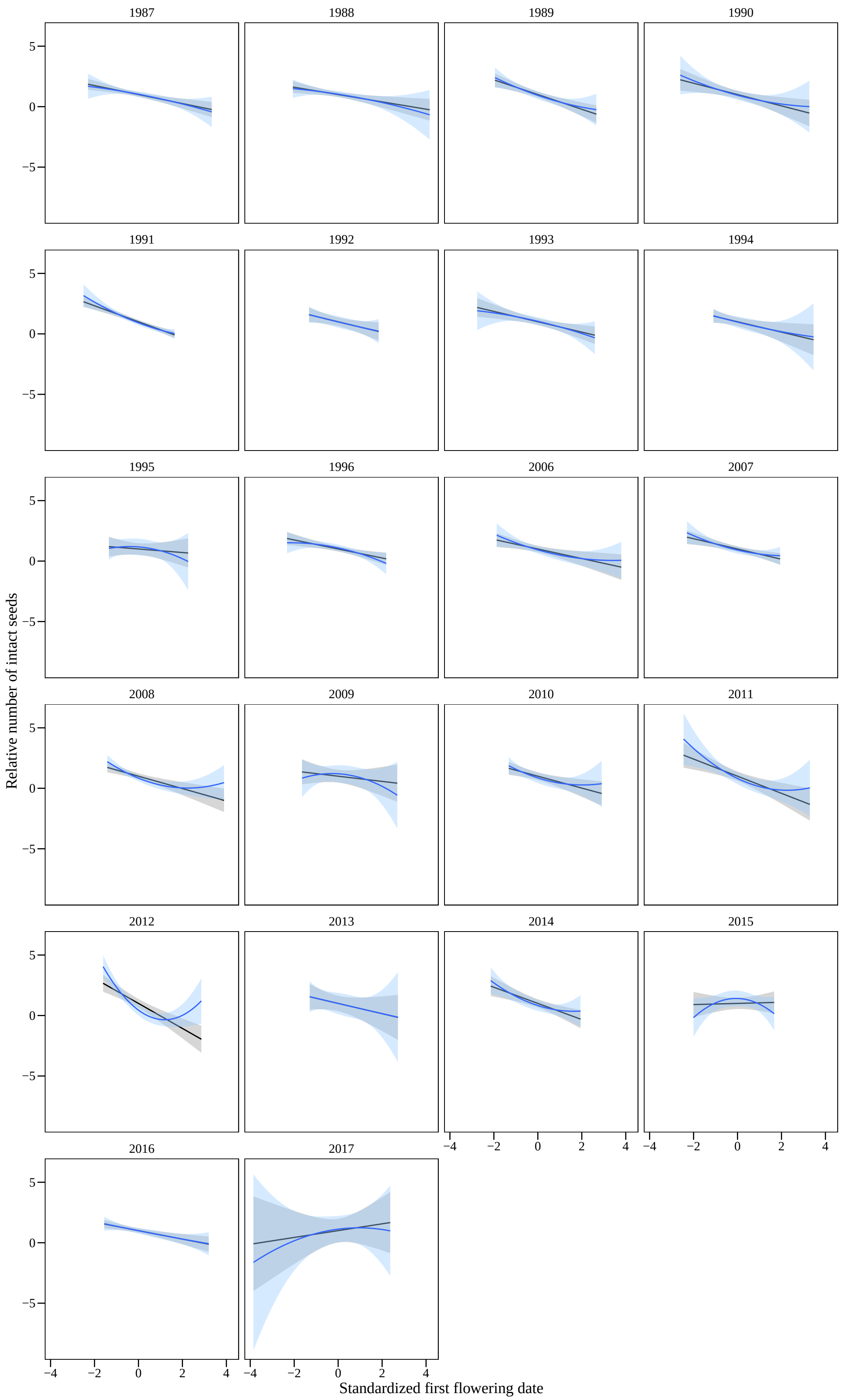
All selection differentials

```
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)])
```

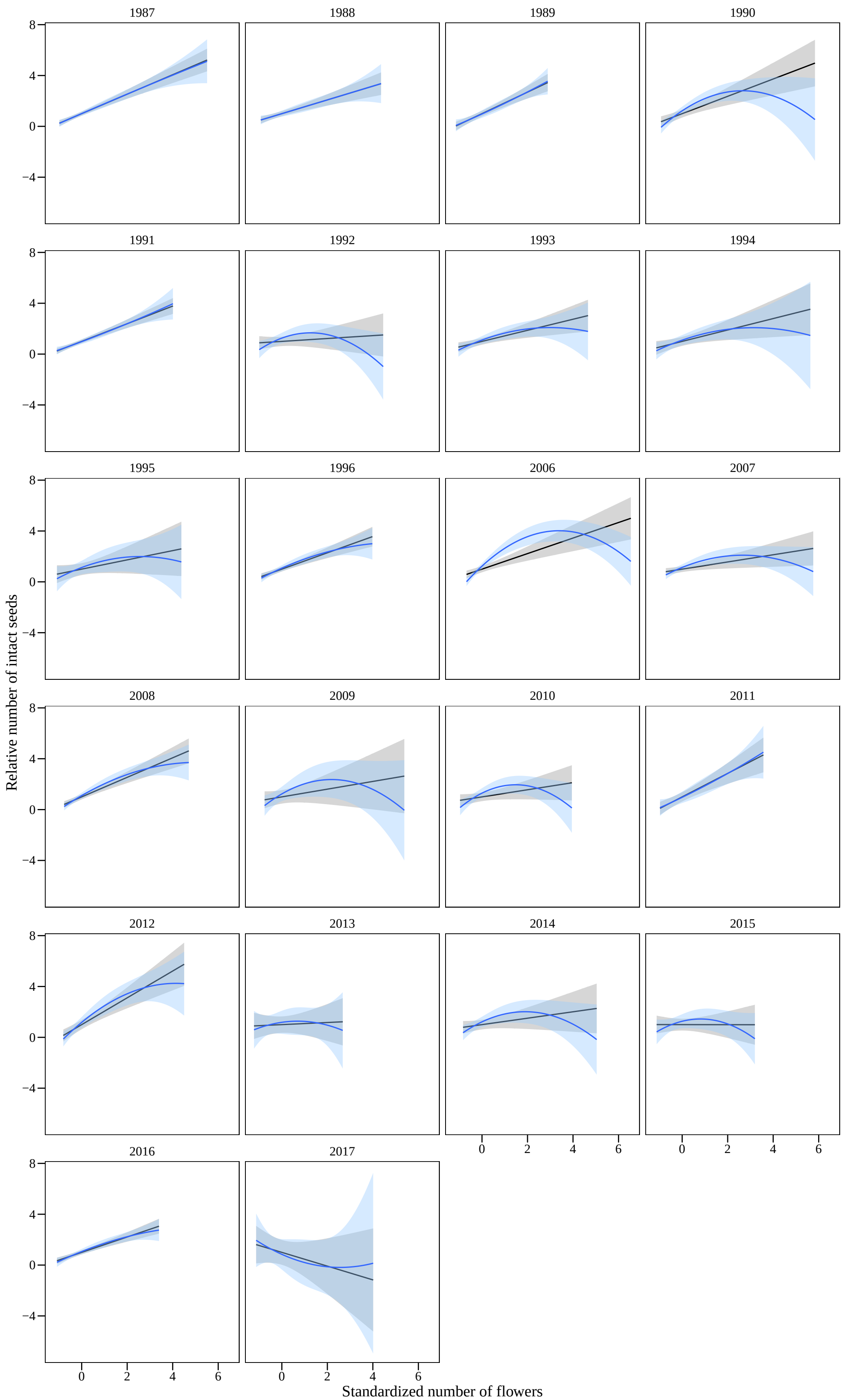
## Plots


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 date
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 date


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 | |

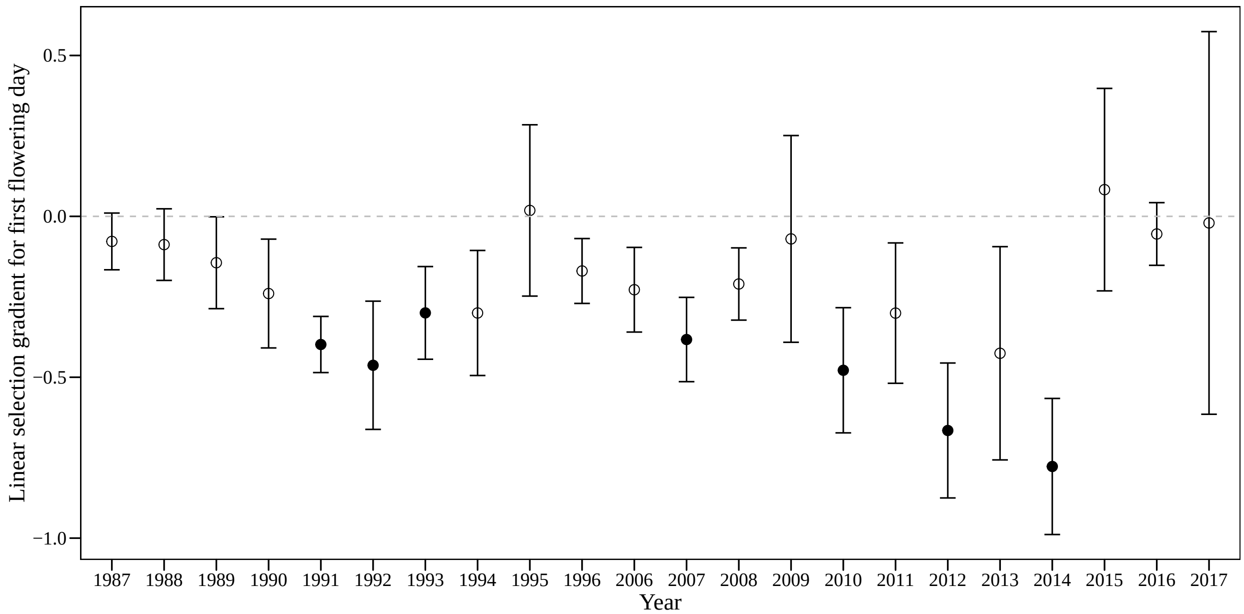
| | year | term | estimate | std.error | statistic | p.value | sig |
|---|---|---|---|---|---|---|---|
| 39 | 1993 | I(FFD_std^2) | 0.021 | 0.119 | 0.173 | 0.863 | |
| 45 | 1994 | I(FFD_std^2) | -0.018 | 0.171 | -0.104 | 0.917 | |
| 51 | 1995 | I(FFD_std^2) | -0.229 | 0.308 | -0.743 | 0.462 | |
| 57 | 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)

## Results 1: Among-year variation and trends

### Trends

#### Trend in spring temperature

All years

```
with(summarySE(weather_45, measurevar="mean", groupvars=c("year")),tidy(lm(mean~year))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -58.0      38.1         -1.52  0.144
## 2 year          0.0331    0.0190      1.74  0.0974
```

First set of years

```
with(subset(summarySE(weather_45, measurevar="mean", groupvars=c("year")),
            year<2006),tidy(lm(mean~year))) #NS
```

```
## # A tibble: 2 x 5
##   term         estimate std.error statistic p.value
##   <chr>           <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  129.       266.         0.486   0.640
## 2 year          -0.0609     0.133    -0.456   0.660
```

Second set of years

```
with(subset(summarySE(weather_45, measurevar="mean", groupvars=c("year")),
            year>1996),tidy(lm(mean~year))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  27.5      114.          0.241   0.815
## 2 year         -0.00938    0.0568    -0.165   0.872
```

### Trend in FFD

All years

```
data_sel$year_int<-as.integer(as.character(data_sel$year))
with(summarySE(data_sel, measurevar="FFD", groupvars=c("year_int")),tidy(lm(FFD~year_int))) #*
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  583.      217.          2.69  0.0141
## 2 year_int      -0.262     0.108     -2.42  0.0250
```

First set of years

```
with(subset(summarySE(data_sel, measurevar="FFD", groupvars=c("year_int")),
  year_int<2006),tidy(lm(FFD~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -1694.     1307.         -1.30   0.231
## 2 year_int        0.882     0.656      1.34   0.216
```

Second set of years

```
with(subset(summarySE(data_sel, measurevar="FFD", groupvars=c("year_int")),
  year_int>1996),tidy(lm(FFD~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -250.      622.       -0.402   0.696
## 2 year_int       0.152     0.309     0.490   0.634
```

### RESIDUALS FFD~TEMP UNRELATED TO YEAR

```
with(merge(summarySE(data_sel, measurevar="FFD", groupvars=c("year_int")),
      summarySE(data_sel, measurevar="mean_45", groupvars=c("year_int"))[c(1,3)]),
     tidy(lm(residuals(lm(FFD~mean_45))~year_int)))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  173.      110.          1.57   0.132
## 2 year_int      -0.0865    0.0550    -1.57   0.132
```

### RESIDUALS FFD RELATED TO RESIDUALS TEMP

```
with(merge(summarySE(data_sel, measurevar="FFD", groupvars=c("year_int")),
      summarySE(data_sel, measurevar="mean_45", groupvars=c("year_int"))[c(1,3)]),
     tidy(lm(residuals(lm(FFD~year_int))~residuals(lm(mean_45~year_int)))))
```

```
## # A tibble: 2 x 5
##   term                             estimate std.error statistic    p.value
##   <chr>                               <dbl>     <dbl>     <dbl>      <dbl>
## 1 (Intercept)                      6.54e-16     0.570  1.15e-15   10.00e-1
## 2 residuals(lm(mean_45 ~ year_in~ -4.91e+ 0     0.640 -7.67e+ 0    2.22e-7
```

### Trend in fitness

All years

```
with(summarySE(data_sel, measurevar="n_intact_seeds",groupvars=c("year_int")),
     tidy(lm(n_intact_seeds~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  27.3     177.         0.154   0.879
## 2 year_int     -0.0112    0.0883    -0.127   0.901
```

First set of years

```
with(subset(summarySE(data_sel, measurevar="n_intact_seeds",groupvars=c("year_int")),year_int<2006),
     tidy(lm(n_intact_seeds~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  821.      526.         1.56   0.157
## 2 year_int      -0.410     0.264     -1.55   0.159
```

Second set of years

```
with(subset(summarySE(data_sel, measurevar="n_intact_seeds",groupvars=c("year_int")),year_int>1996),
     tidy(lm(n_intact_seeds~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  850.      903.        0.941   0.369
## 2 year_int      -0.420     0.449    -0.935   0.372
```

### Trend in selection gradients for FFD

All years

```
selgrads_FFD$year_int<-as.integer(as.character(selgrads_FFD$year))
with(subset(selgrads_FFD,term=="FFD_std"),tidy(lm(estimate~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
```

```
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  5.80      9.05        0.641   0.529
## 2 year_int    -0.00303   0.00452    -0.670   0.511
```

First set of years

```r
with(subset(selgrads_FFD,term=="FFD_std"&year_int<2006),tidy(lm(estimate~year_int))) #NS
```

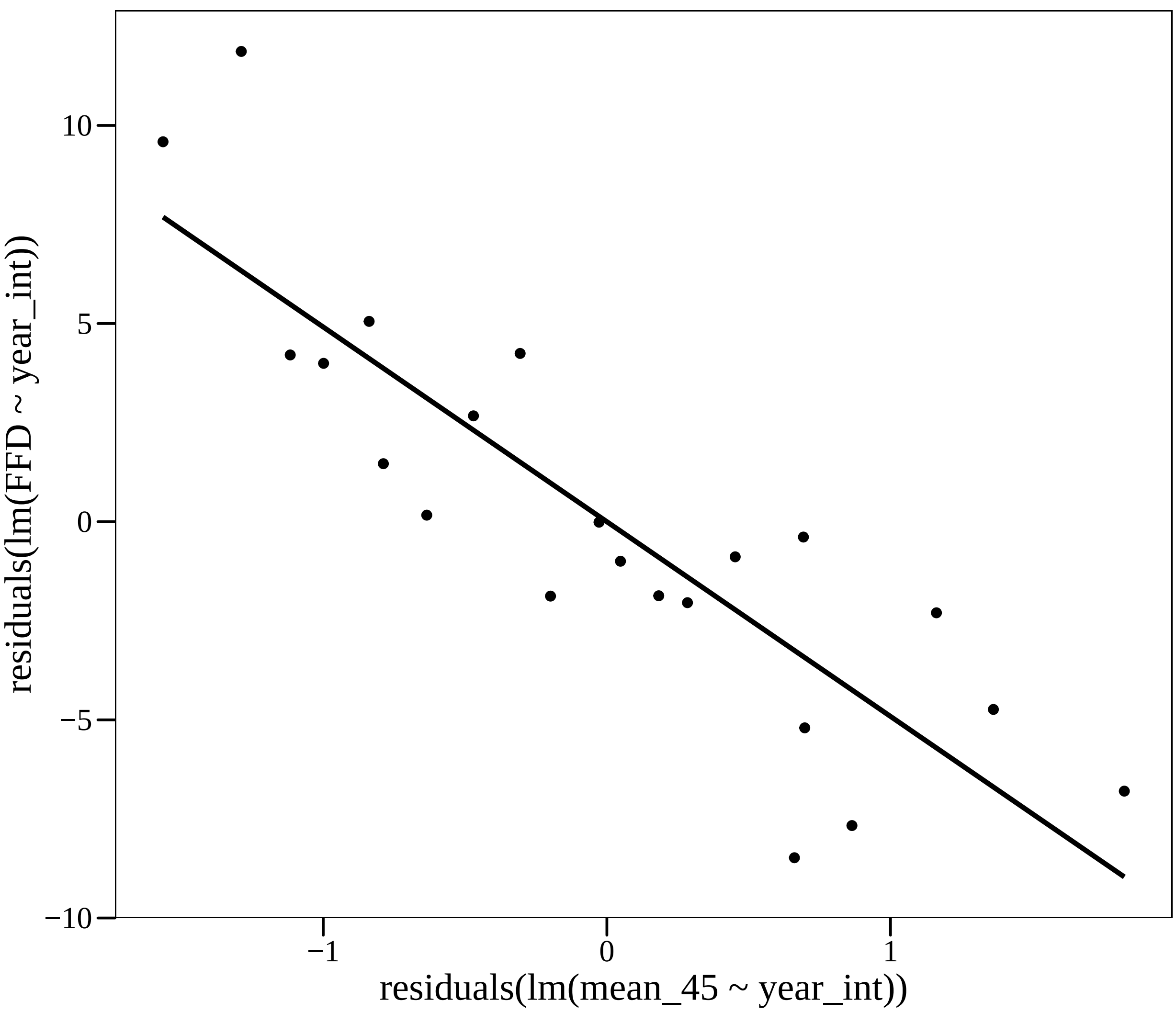
```
## # A tibble: 2 x 5
##   term         estimate std.error statistic p.value
##   <chr>           <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  13.2       34.9        0.377   0.716
## 2 year_int     -0.00672    0.0175    -0.384   0.711
```

Second set of years

```r
with(subset(selgrads_FFD,term=="FFD_std"&year_int>1996),tidy(lm(estimate~year_int))) #NS
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -25.2      45.9       -0.550   0.595
## 2 year_int      0.0124    0.0228     0.543   0.599
```

#### PLOT RESIDUALS FFD AGAINST RESIDUALS TEMP




### Proprtion of variation explained by year

#### FFD

```
with(data_sel,summary(lm(FFD~year))) #* Linear model, year=factor, Adjusted R-squared:  0.5836
```

```
##
## Call:
## lm(formula = FFD ~ year)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -15.0833  -3.3083  -0.3107   2.7421  22.7284
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  66.2559     0.3066 216.070  < 2e-16 ***
## year1988     -6.3480     0.4742 -13.386  < 2e-16 ***
## year1989    -12.4002     0.5678 -21.839  < 2e-16 ***
## year1990    -11.7935     0.5121 -23.028  < 2e-16 ***
## year1991     -1.2608     0.4673  -2.698  0.00702 **
## year1992     -6.4054     0.5357 -11.958  < 2e-16 ***
## year1993    -10.5188     0.4695 -22.403  < 2e-16 ***
## year1994     -6.0558     0.4623 -13.100  < 2e-16 ***
## year1995      3.2810     0.7917   4.144 3.53e-05 ***
## year1996      5.2983     0.5239  10.112  < 2e-16 ***
## year2006     -7.7275     0.5763 -13.409  < 2e-16 ***
## year2007    -14.6554     0.5763 -25.431  < 2e-16 ***
## year2008    -18.1954     0.6085 -29.900  < 2e-16 ***
## year2009    -10.3651     0.6789 -15.268  < 2e-16 ***
## year2010     -7.5692     0.6296 -12.021  < 2e-16 ***
## year2011    -12.8012     0.5952 -21.508  < 2e-16 ***
## year2012    -10.5993     0.5454 -19.434  < 2e-16 ***
## year2013     -6.7810     0.6468 -10.484  < 2e-16 ***
## year2014    -12.2865     0.6703 -18.331  < 2e-16 ***
## year2015    -13.4203     0.8460 -15.864  < 2e-16 ***
## year2016    -13.8570     0.5437 -25.485  < 2e-16 ***
## year2017     -7.0210     0.5172 -13.575  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.731 on 2452 degrees of freedom
## Multiple R-squared:  0.5871, Adjusted R-squared:  0.5836
## F-statistic:   166 on 21 and 2452 DF,  p-value: < 2.2e-16
```

```
with(data_sel,summary(lmer(FFD~(1|year)))) #* Linear mixed model, year=factor
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: FFD ~ (1 | year)
##
## REML criterion at convergence: 14818.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.1831 -0.7083 -0.0674  0.5806  4.7878
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  year     (Intercept) 34.45    5.869
##  Residual             22.38    4.731
## Number of obs: 2474, groups:  year, 22
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   58.010      1.256   46.19
```

```
r.squaredGLMM(lmer(FFD~(1|year),data_sel)) # 0.6062021
```

```
## Warning: 'r.squaredGLMM' now calculates a revised statistic. See the help
## page.
```

```
##      R2m       R2c
```

```
## [1,]   0 0.6062021
```

```r
r.squaredLR(lmer(FFD~(1|year),data_sel)) # 0.5650669
```

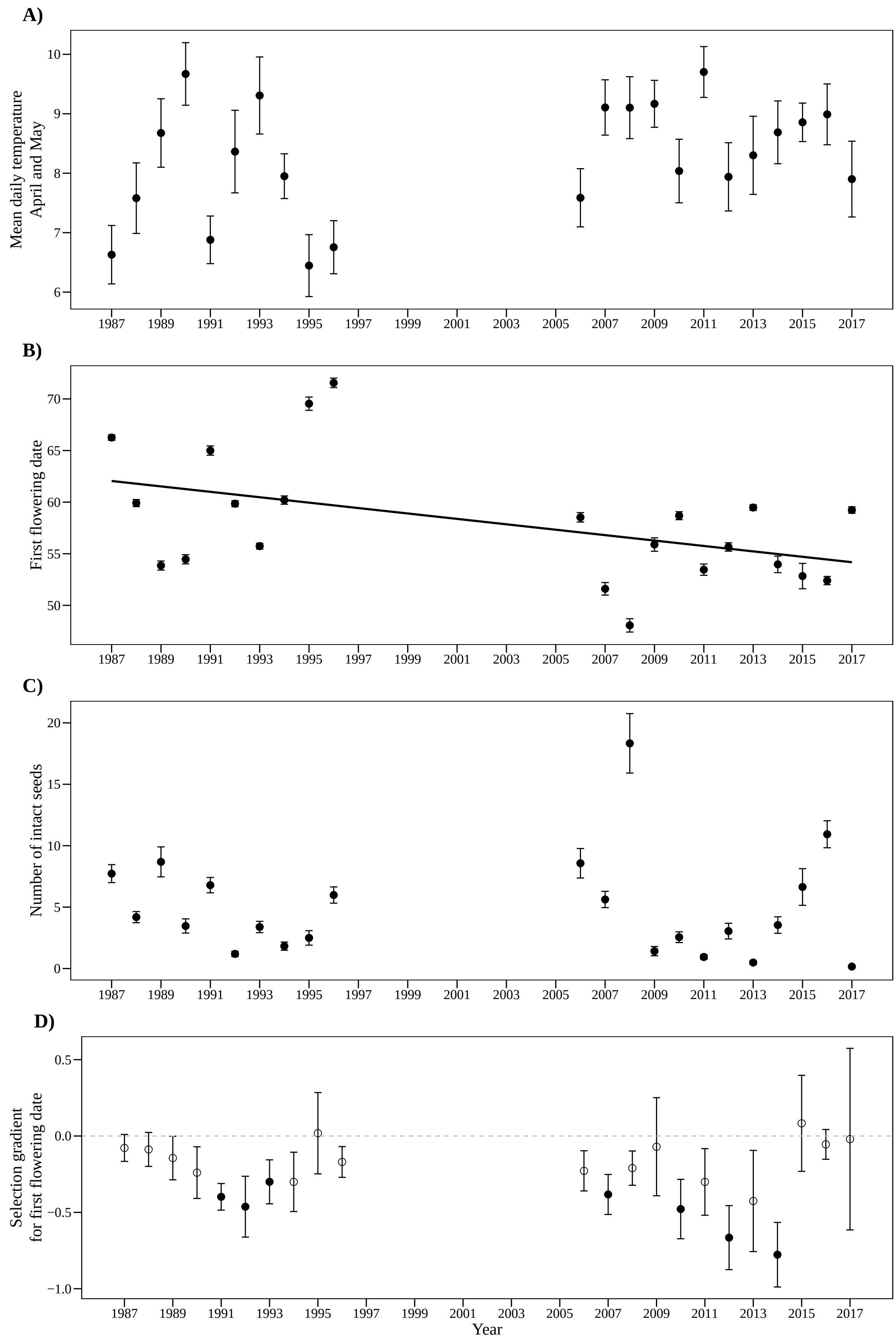
```
## [1] 0.564451
## attr(,"adj.r.squared")
## [1] 0.5650669
```

### Fitness

```r
with(data_sel,summary(lm(n_intact_seeds~year))) #* Linear model, year=factor, Adjusted R-squared:  0.16
```

```
##
## Call:
## lm(formula = n_intact_seeds ~ year)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.332  -3.540  -1.415   1.618  88.274
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.7259     0.5358  14.418  < 2e-16 ***
## year1988     -3.5421     0.8287  -4.274 1.99e-05 ***
## year1989      0.9577     0.9922   0.965 0.334499
## year1990     -4.2609     0.8949  -4.761 2.04e-06 ***
## year1991     -0.9378     0.8166  -1.148 0.250890
## year1992     -6.5356     0.9361  -6.982 3.73e-12 ***
## year1993     -4.3438     0.8205  -5.294 1.30e-07 ***
## year1994     -5.9031     0.8078  -7.308 3.66e-13 ***
## year1995     -5.2326     1.3835  -3.782 0.000159 ***
## year1996     -1.7421     0.9155  -1.903 0.057188 .
## year2006      0.8449     1.0070   0.839 0.401530
## year2007     -2.1040     1.0070  -2.089 0.036784 *
## year2008     10.6065     1.0634   9.974  < 2e-16 ***
## year2009     -6.3109     1.1863  -5.320 1.13e-07 ***
## year2010     -5.1741     1.1003  -4.703 2.71e-06 ***
## year2011     -6.7883     1.0401  -6.527 8.13e-11 ***
## year2012     -4.6805     0.9531  -4.911 9.66e-07 ***
## year2013     -7.2380     1.1303  -6.404 1.81e-10 ***
## year2014     -4.1862     1.1712  -3.574 0.000358 ***
## year2015     -1.0870     1.4783  -0.735 0.462203
## year2016      3.2049     0.9501   3.373 0.000755 ***
## year2017     -7.5673     0.9038  -8.373  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.267 on 2452 degrees of freedom
## Multiple R-squared:  0.176,  Adjusted R-squared:  0.1689
## F-statistic: 24.93 on 21 and 2452 DF,  p-value: < 2.2e-16
```

**Fig. 1**


A)
Mean daily temperature
April and May
B)
First flowering date
C)
Number of intact seeds
D)
Selection gradient
for first flowering date
Year

# Results 2: Response of FFD for each plant, mean position and duration of flowering to temperature

## FFD for each plant

```
tidy(lm(FFD ~ mean_45,data = data_sel))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)    99.6      0.895     111.        0
## 2 mean_45        -5.01     0.109     -45.8       0
```

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

```
## [1] 0.4587361
```

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

```
##        1
## 67.25939
```

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

```
##        1
## 50.95233
```

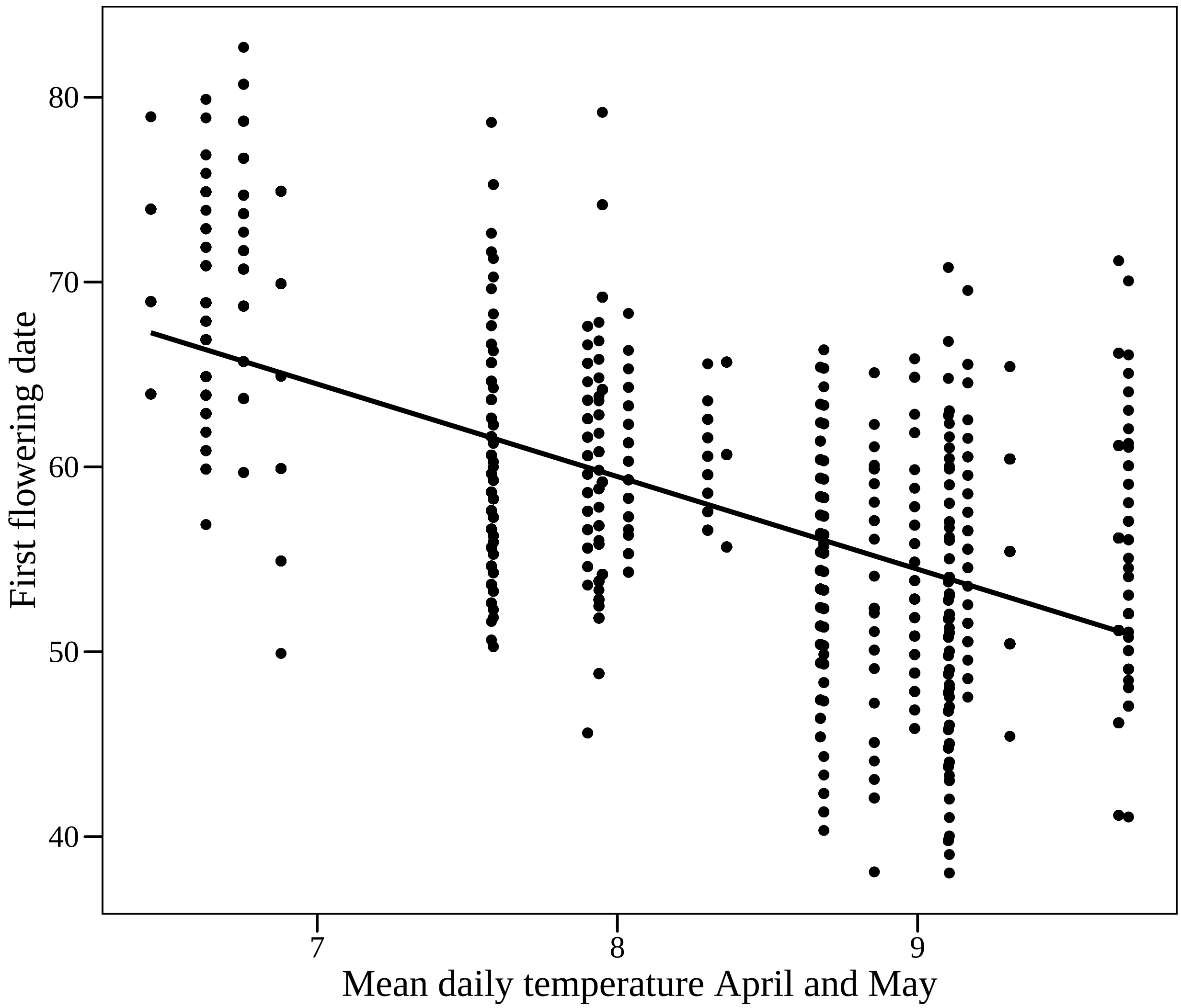
```
## FFD also related to temp when including year (Supp. mat)
tidy(lm(FFD ~ mean_45+as.integer(year),data = data_sel))
```

```
## # A tibble: 3 x 5
##   term             estimate std.error statistic   p.value
##   <chr>               <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)        98.6      0.901      109.   0.
## 2 mean_45            -4.77     0.116      -41.2  2.54e-283
## 3 as.integer(year)   -0.107    0.0175      -6.10 1.20e-  9
```

```
glance(lm(FFD~mean_45+as.integer(year),data=data_sel))$adj.r.squared # Rsquare
```

```
## [1] 0.4665613
```

**Fig. 2: Response of FFD for each plant to spring temperature**




### Position

```
tidy(lm(FFD_mean~mean_45,data=mean_weather7))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   102.       5.30      19.2  2.36e-14
## 2 mean_45        -5.31     0.638     -8.32 6.38e- 8
```

```
glance(lm(FFD_mean~mean_45,data=mean_weather7))$adj.r.squared # Rsquare
```

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

```
predict(lm(FFD_mean~mean_45,data=mean_weather7),
        data.frame(mean_45=with(mean_weather7,min(mean_45)))) # Coldest
```

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

```r
predict(lm(FFD_mean~mean_45,data=mean_weather7),
        data.frame(mean_45=with(mean_weather7,max(mean_45)))) # Warmest
```

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

```r
## FFD_mean also related to temp when including year  (Supp. mat)
tidy(lm(FFD_mean~mean_45+year,data=mean_weather7))
```

```
## # A tibble: 3 x 5
##   term         estimate std.error statistic     p.value
##   <chr>           <dbl>     <dbl>     <dbl>       <dbl>
## 1 (Intercept)  297.      118.          2.52 0.0210
## 2 mean_45       -4.91      0.657      -7.48 0.000000448
## 3 year          -0.0993    0.0600     -1.66 0.114
```

```r
glance(lm(FFD_mean~mean_45+year,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.7833063
```

```r
tidy(lm(date_10~mean_45,data=mean_weather7))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    98.7      6.70      14.7  3.40e-12
## 2 mean_45        -5.74     0.807     -7.11 6.85e- 7
```

```r
glance(lm(date_10~mean_45,data=mean_weather7))$adj.r.squared # Rsquare
```

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

```r
predict(lm(date_10~mean_45,data=mean_weather7),
        data.frame(mean_45=with(mean_weather7,min(mean_45)))) # Coldest
```

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

```r
predict(lm(date_10~mean_45,data=mean_weather7),
        data.frame(mean_45=with(mean_weather7,max(mean_45)))) # Warmest
```

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

```r
## date_10 also related to temp when including year (Supp. mat)
tidy(lm(date_10~mean_45+year,data=mean_weather7))
```

```
## # A tibble: 3 x 5
##   term         estimate std.error statistic    p.value
##   <chr>           <dbl>     <dbl>     <dbl>      <dbl>
## 1 (Intercept)  261.      155.          1.68 0.109
## 2 mean_45       -5.41      0.863      -6.26 0.00000516
## 3 year          -0.0826    0.0789     -1.05 0.308
```

```r
glance(lm(date_10~mean_45+year,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.7038144
```

```r
tidy(lm(date_90~mean_45,data=mean_weather7))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   103.       5.13      20.1  9.56e-15
## 2 mean_45        -4.89     0.617     -7.93 1.35e- 7
```

```r
glance(lm(date_90~mean_45,data=mean_weather7))$adj.r.squared # Rsquare
```

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

```r
predict(lm(date_90~mean_45,data=mean_weather7),
        data.frame(mean_45=with(mean_weather7,min(mean_45)))) # Coldest
```

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

```r
predict(lm(date_90~mean_45,data=mean_weather7),
        data.frame(mean_45=with(mean_weather7,max(mean_45)))) # Warmest
```

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

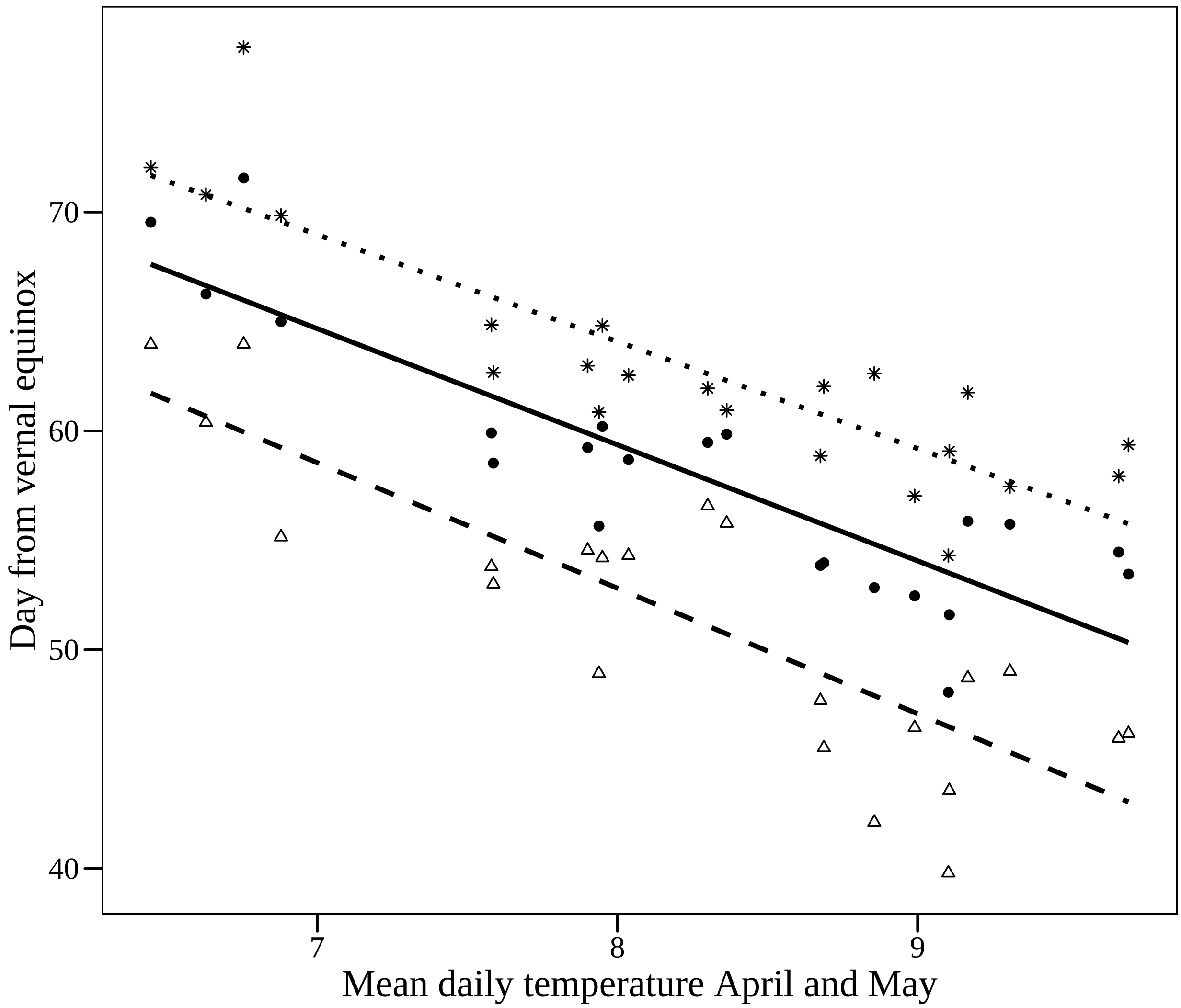
```r
## date_90 also related to temp when including year (Supp. mat)
tidy(lm(date_90~mean_45+year,data=mean_weather7))
```

```
## # A tibble: 3 x 5
##   term         estimate std.error statistic     p.value
##   <chr>           <dbl>     <dbl>     <dbl>       <dbl>
## 1 (Intercept)  158.      122.          1.30  0.209
## 2 mean_45       -4.78      0.675     -7.07  0.000000990
## 3 year          -0.0280    0.0617    -0.453 0.656
```

```r
glance(lm(date_90~mean_45+year,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.7359362
```

**Fig. 3: Response of position to spring temperature**




## Duration

```
tidy(lm(days_90_10~mean_4,data=mean_weather7))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    0.928     2.42      0.383 0.706
## 2 mean_4         1.87      0.417     4.48  0.000229
```

```
tidy(lm(days_90_10~mean_45,data=mean_weather7))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)    4.49      6.72      0.669   0.511
## 2 mean_45        0.847     0.808     1.05    0.307
```

```
tidy(lm(days_90_10~mean_5,data=mean_weather7))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   21.3       5.81       3.66 0.00157
## 2 mean_5        -0.906     0.535     -1.69 0.106
```

```
glance(lm(days_90_10~mean_4,data=mean_weather7))$adj.r.squared # Rsquare
```

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

```
glance(lm(days_90_10~mean_45,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.004676164
```

```
glance(lm(days_90_10~mean_5,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.08172378
```

```
predict(lm(days_90_10~mean_4,data=mean_weather7),
        data.frame(mean_4=with(mean_weather7,min(mean_4)))) # Coldest
```

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

```
predict(lm(days_90_10~mean_4,data=mean_weather7),
        data.frame(mean_4=with(mean_weather7,max(mean_4)))) # Warmest
```

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

```
## days_90_10 also related to temp when including year (Supp. mat)
tidy(lm(days_90_10~mean_4+year,data=mean_weather7))
```

```
## # A tibble: 3 x 5
##   term         estimate std.error statistic  p.value
##   <chr>           <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)  20.5      117.          0.176 0.862
## 2 mean_4        1.90       0.457      4.15  0.000542
## 3 year         -0.00985    0.0586    -0.168 0.868
```

```
tidy(lm(days_90_10~mean_45+year,data=mean_weather7))
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -103.      158.       -0.652   0.522
## 2 mean_45        0.630     0.879     0.717   0.482
## 3 year           0.0547    0.0803    0.681   0.504
```

```
tidy(lm(days_90_10~mean_5+year,data=mean_weather7))
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -173.      140.        -1.24   0.231
## 2 mean_5        -1.03      0.530     -1.94   0.0679
## 3 year           0.0976    0.0702     1.39   0.181
```

```r
glance(lm(days_90_10~mean_4+year,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.4491733
```

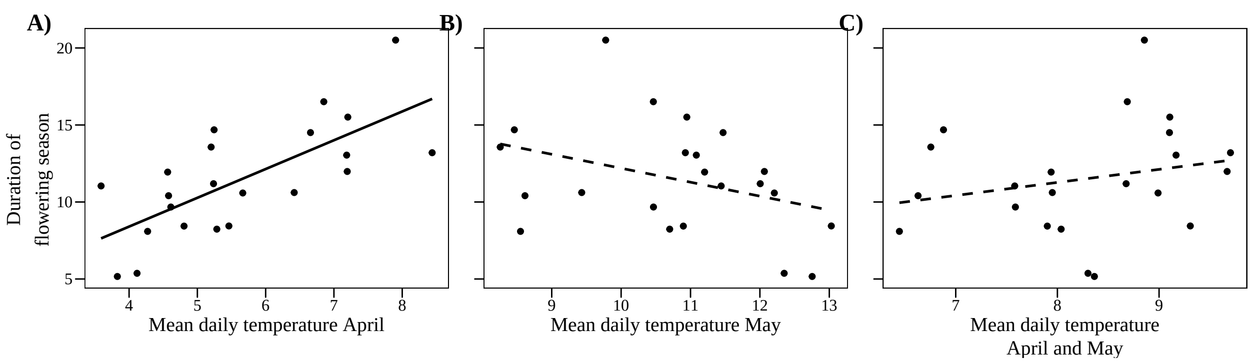
```r
glance(lm(days_90_10~mean_45+year,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] -0.0227632
```

```r
glance(lm(days_90_10~mean_5+year,data=mean_weather7))$adj.r.squared # Rsquare
```

```
## [1] 0.1226226
```

**Fig. 4: Response of duration of the flowering season to spring temperature**




# Results 3 NEW: Response of fitness to spring temperature, mean position and duration of flowering

## Spring temperature

```r
tidy(lm(n_intact_seeds ~ mean_45+n_fl,data = data_sel)) #*
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    7.43     1.39        5.35 9.54e- 8
## 2 mean_45       -0.628    0.170      -3.69 2.30e- 4
## 3 n_fl           0.195    0.00936    20.8  1.65e-88
```

```r
glance(lm(n_intact_seeds ~ mean_45+n_fl,data = data_sel))$adj.r.squared # Rsquare
```

```
## [1] 0.1493946
```

## Position

```r
tidy(lm(n_intact_seeds~FFD_mean+n_fl,data=data_sel)) #NS
```

```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
```

```
## 1 (Intercept)  2.09       1.83         1.14  2.54e- 1
## 2 FFD_mean     0.00470    0.0305       0.154 8.77e- 1
## 3 n_fl         0.192      0.00950     20.2   2.06e-84
```

```
glance(lm(n_intact_seeds~FFD_mean+n_fl,data=data_sel))$adj.r.squared # Rsquare
```

```
## [1] 0.1447179
```

### Duration

```
tidy(lm(n_intact_seeds~days_90_10+n_fl,data=data_sel)) #*
```

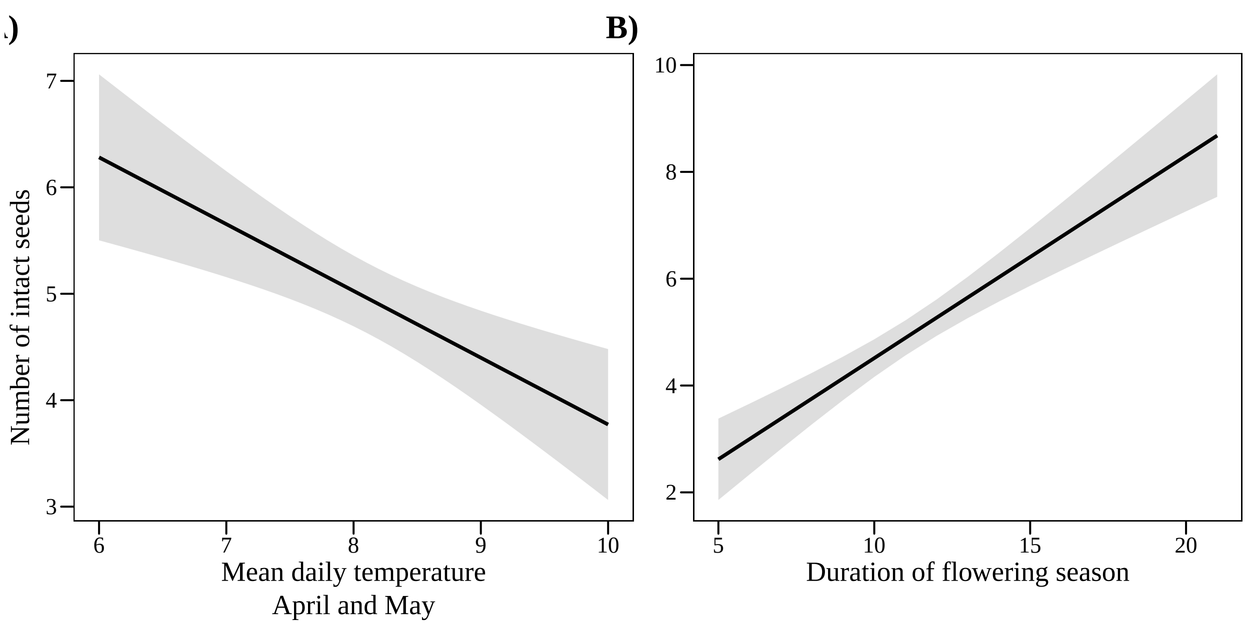
```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)   -1.78     0.657      -2.70 6.88e- 3
## 2 days_90_10     0.379    0.0569      6.65 3.54e-11
## 3 n_fl           0.186    0.00933    19.9  8.42e-82
```

```
glance(lm(n_intact_seeds~days_90_10+n_fl,data=data_sel))$adj.r.squared # Rsquare
```

```
## [1] 0.159758
```

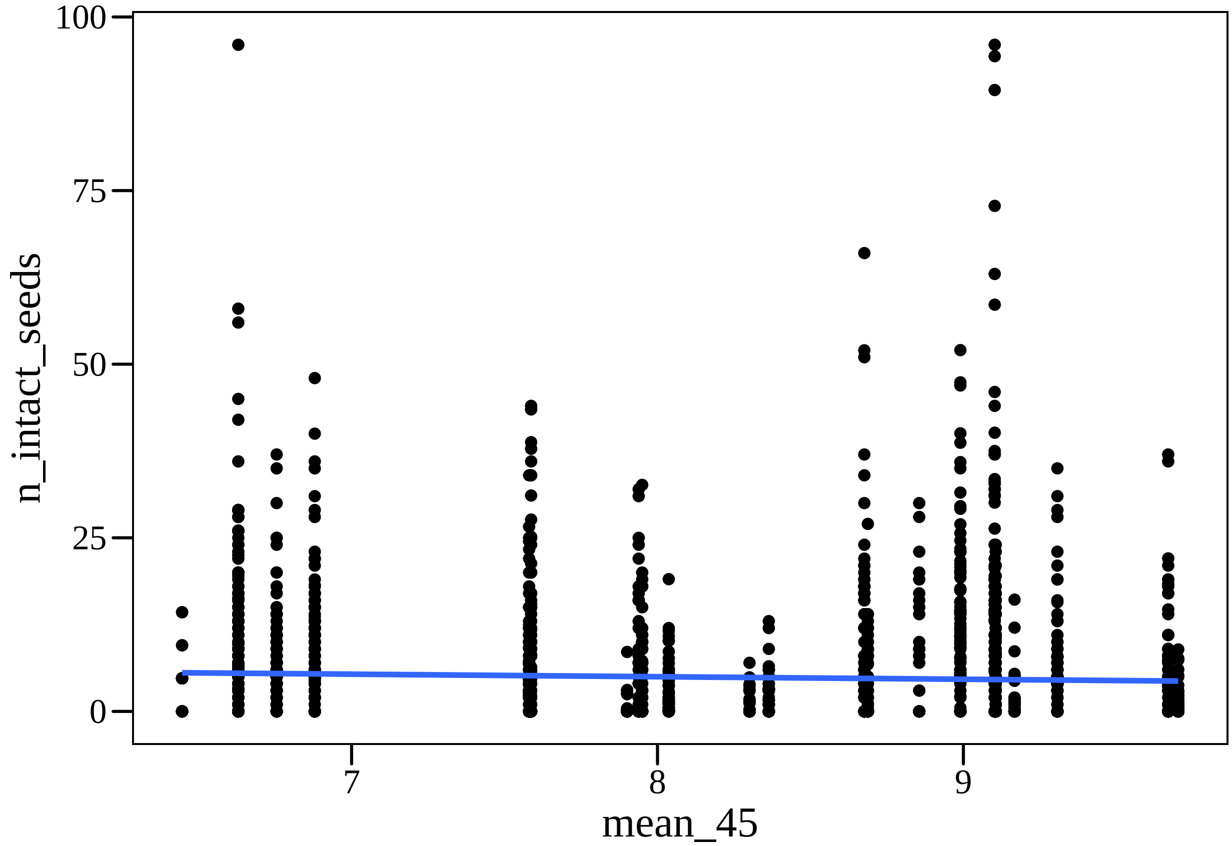
### Fig. 5: Response of fitness to spring temperature, mean position and duration of flowering

Graphs of the effect of variables taking into account that number of flowers is included in the model

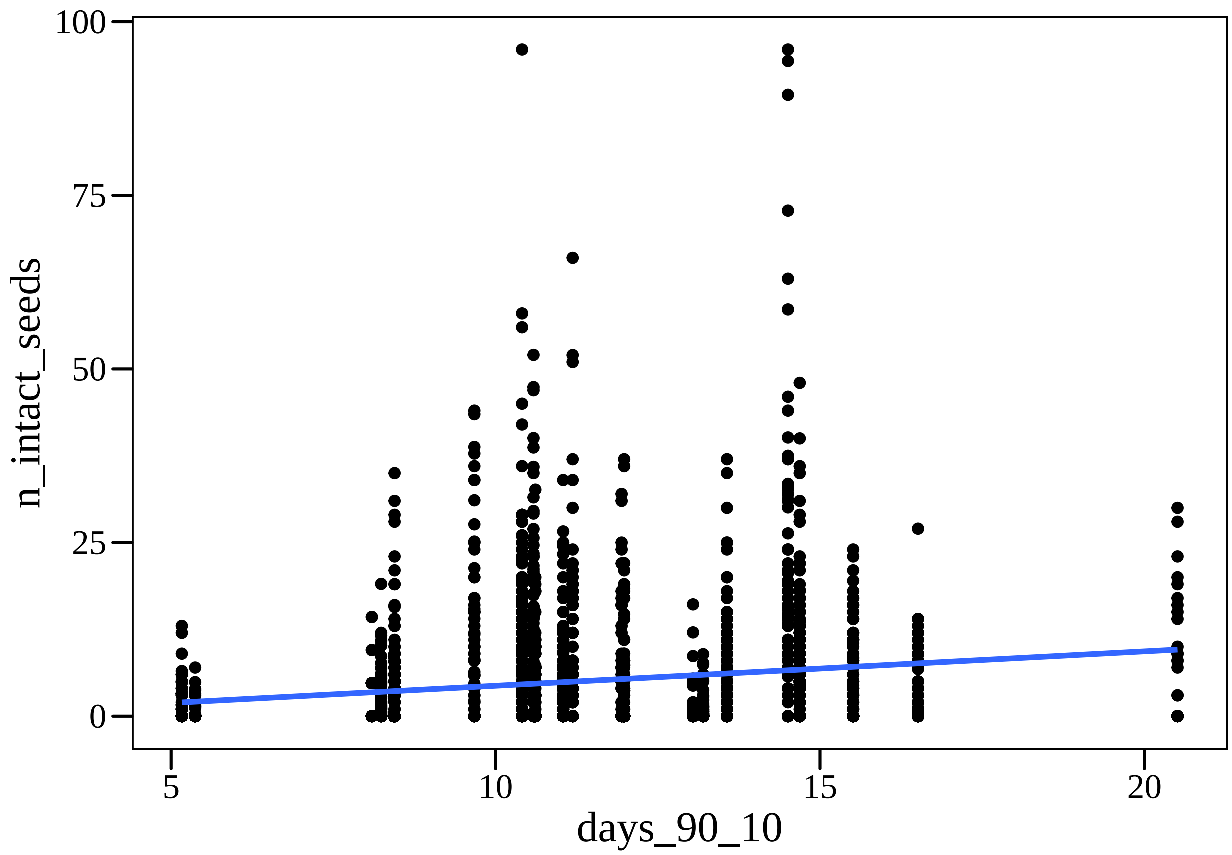



Graphs with raw data

```
# Spring temperature, fitness for each plant
ggplot(data_sel,aes(x=mean_45,y=n_intact_seeds))+
  geom_point()+geom_smooth(method="lm",se=F)+my_theme()
```




```r
# Duration
ggplot(data_sel,aes(x=days_90_10,y=n_intact_seeds))+
  geom_point()+geom_smooth(method="lm",se=F)+my_theme()
```




## Results 4: Differences in selection among years

### Indirect selection (selection differentials)

```
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
```

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

### Direct selection (selection gradients)

```
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 5: Are differences in selection among years related to climatic conditions?

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

```r
mean_weather8<-merge(mean_weather7,subset(selgrads_FFD,term=="FFD_std")[c(1,3)])
names(mean_weather8)[241]<-"selgrad_FFD"
mean_weather8<-merge(mean_weather8,subset(seldiffs_FFD,term=="FFD_std")[c(1,3)])
names(mean_weather8)[242]<-"seldiff_FFD"
```

## Analysis with selection gradients (not used)

### Spring temperature

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  -0.0169    0.412    -0.0410   0.968
## 2 mean_45      -0.0293    0.0496   -0.590    0.562
```

```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))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.479     0.379      -1.26    0.221
## 2 date_10      0.00429   0.00732     0.586   0.564
```

```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))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.616     0.478      -1.29    0.212
## 2 FFD_mean     0.00616   0.00819     0.752   0.461
```

```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))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.739     0.552      -1.34    0.195
## 2 date_90      0.00765   0.00875     0.874   0.392
```

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

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

### Duration of the flowering season

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.295      0.162     -1.83   0.0829
## 2 days_90_10   0.00319    0.0135     0.237  0.815
```

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

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

## Analysis with selection differentials (not used)

### Spring temperature

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  -0.132     0.501     -0.262   0.796
## 2 mean_45      -0.0343    0.0603    -0.569   0.576
```

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

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

### Position of the flowering season

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.810     0.456      -1.78   0.0909
## 2 date_10      0.00769   0.00881     0.873  0.393
```

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

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

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.886     0.579      -1.53    0.141
## 2 FFD_mean     0.00812   0.00993     0.818   0.423
```

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

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

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.991      0.671     -1.48    0.155
## 2 date_90      0.00916    0.0106     0.862   0.399
```

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

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

### Duration of the flowering season

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

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.361      0.197     -1.84   0.0809
## 2 days_90_10  -0.00466    0.0163    -0.285  0.779
```

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

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

## GLMMs (not used)

```r
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
```

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

## GLMs

```r
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:mean_45+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 29.9759 4.816e-08 ***
## n_fl_std          293.5    1 72.2770 < 2.2e-16 ***
## FFD_std:mean_45     0.6    1  0.1552    0.6937
## Residuals       10029.7 2470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```r
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:date_10+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  29.986 4.792e-08 ***
## n_fl_std          290.3    1  71.521 < 2.2e-16 ***
## FFD_std:date_10     4.0    1   0.984    0.3213
## Residuals       10026.3 2470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```r
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:FFD_mean+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 29.9784  4.81e-08 ***
## n_fl_std           292.2    1 71.9743 < 2.2e-16 ***
## FFD_std:FFD_mean     1.5    1  0.3614    0.5478
## Residuals        10028.8 2470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```r
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:date_90+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 29.9772 4.813e-08 ***
## n_fl_std          293.2    1 72.2185 < 2.2e-16 ***
## FFD_std:date_90     1.1    1  0.2619    0.6089
## Residuals       10029.2 2470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```r
Anova(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:days_90_10+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  29.987 4.788e-08 ***
## n_fl_std             289.3    1  71.278 < 2.2e-16 ***
## FFD_std:days_90_10     4.4    1   1.096    0.2953
## Residuals          10025.9 2470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

## Fig. 6: Response of selection gradients to spring temperature, position and duration of flowering season