Results Lathyrus paper 1

Contents

Temperature and precipitation data manipulation

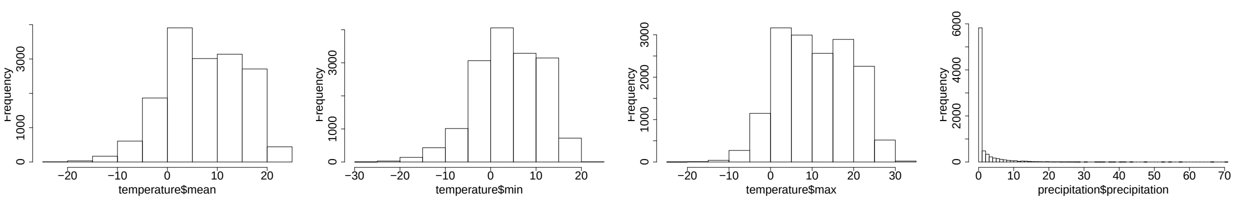
Temperature (daily mean, minimum and maximum) from two stations: Oxelösund and Södertalje
Precipitation from one station: Åda

station	date	year	month	day	mean	quality_mean	min	quality_.min	max	quality_max
Oxelösund	1987-01-01	1987	1	1	-11.6	Y	-14.5	G	-9.0	G
Oxelösund	1987-01-02	1987	1	2	-10.4	Y	-16.5	G	-7.8	G
Oxelösund	1987-01-03	1987	1	3	-9.9	Y	-11.8	G	-8.3	G
Oxelösund	1987-01-04	1987	1	4	-14.1	Y	-17.0	G	-10.4	G

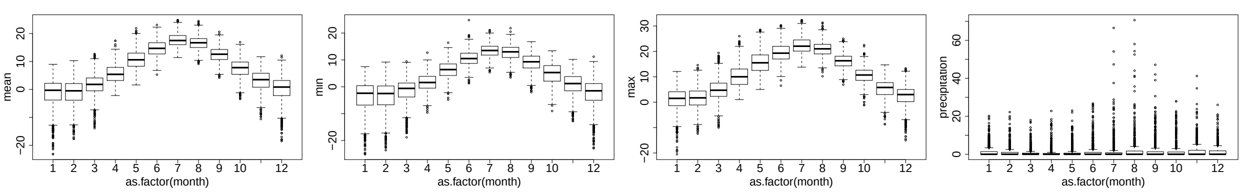
station	date	year	month	day	mean	quality_mean	min	quality__.min	max	quality_max
Oxelösund	1987-01-05	1987	1	5	-4.6	Y	-17.0	G	-1.5	G
Oxelösund	1987-01-06	1987	1	6	-10.7	Y	-14.5	G	-3.0	G

station	date	year	month	day	precipitation	quality
Åda	1987-01-01	1987	1	1	0.0	Y
Åda	1987-01-02	1987	1	2	0.0	Y
Åda	1987-01-03	1987	1	3	0.3	Y
Åda	1987-01-04	1987	1	4	1.1	Y
Åda	1987-01-05	1987	1	5	0.0	Y
Åda	1987-01-06	1987	1	6	2.8	Y

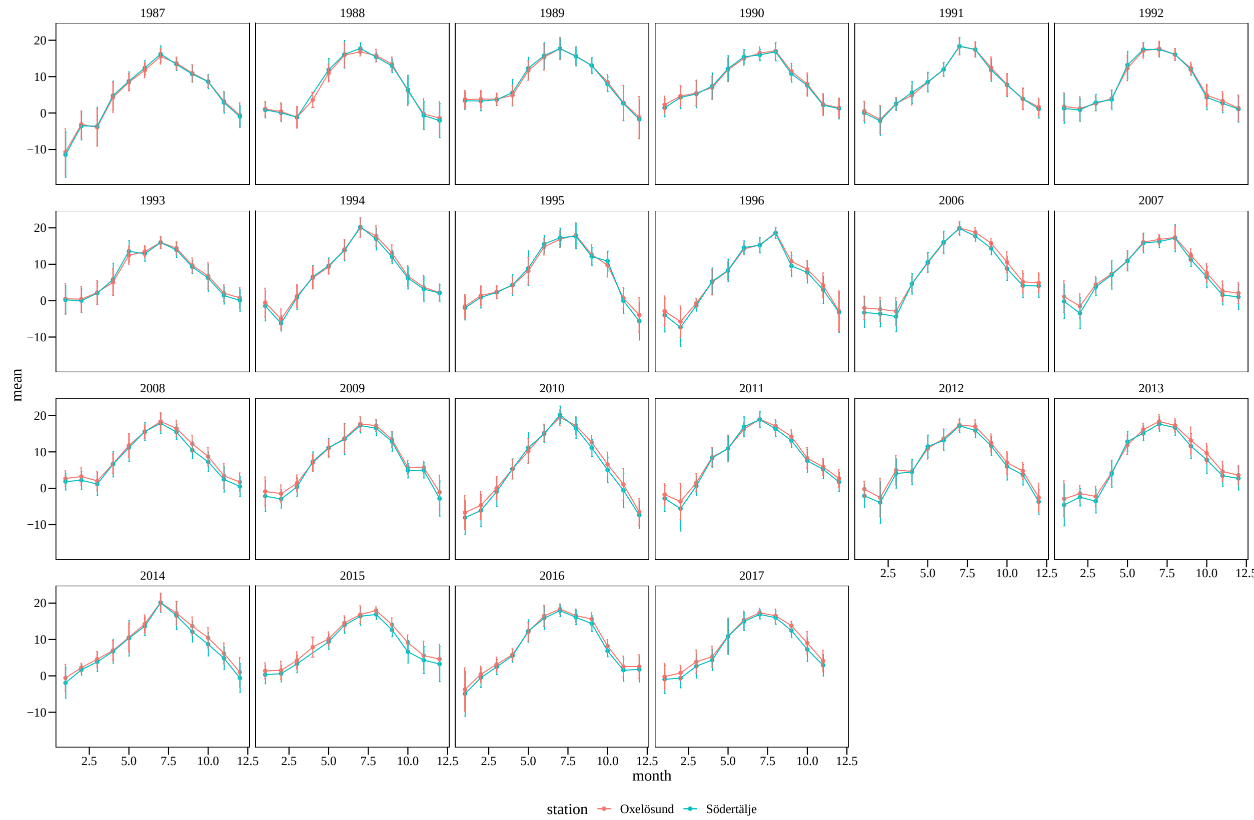
Distributions



Boxplots per month



Comparisons of mean temperatures for each year for both stations



Average mean, min and max temperature of the two stations for further use + join with precipitation data

date	year	month	day	date_ok	mean	min	max	precipitation
1987-01-01	1987	1	1	01/01/1987	-11.25	-14.15	-8.50	0.0
1987-01-02	1987	1	2	02/01/1987	-11.50	-15.25	-7.65	0.0
1987-01-03	1987	1	3	03/01/1987	-10.25	-14.40	-7.90	0.3
1987-01-04	1987	1	4	04/01/1987	-13.35	-16.25	-9.20	1.1
1987-01-05	1987	1	5	05/01/1987	-5.95	-16.50	-2.50	0.0
1987-01-06	1987	1	6	06/01/1987	-11.85	-15.25	-4.25	2.8

```r
nrow(subset(weather,is.na(precipitation))) #154 dates with missing precipitation
```

```
## [1] 154
```

```r
unique(subset(weather,is.na(precipitation))[2:3]) #See which years/months
```

```
##      year month
## 397  1988     2
## 1613 1991     6
## 1858 1992     2
## 2101 1992    10
```

```
## 7970 2017    10
## 7976 2017    11
```

```r
#February 1988, June 1991, February 1992, October 1992 all missing
#Substitute with mean of all years for each specific date
weather$precipitation[is.na(weather$precipitation)&weather$year==1988&weather$month==2]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==2),
  aggregate(precipitation~day,FUN=mean)$precipitation)
weather$precipitation[is.na(weather$precipitation)&weather$year==1991&weather$month==6]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==6),
  aggregate(precipitation~day,FUN=mean)$precipitation)
weather$precipitation[is.na(weather$precipitation)&weather$year==1992&weather$month==2]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==2),
  aggregate(precipitation~day,FUN=mean)$precipitation)
weather$precipitation[is.na(weather$precipitation)&weather$year==1992&weather$month==10]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==10),
  aggregate(precipitation~day,FUN=mean)$precipitation)
#October-November 2017 leave as NAs, will be available later
```

Calculation of GDD and GDH

Bases considered: 3/5/7/10 ºC

GDD:

$$GDD = \max\left(\frac{T_{\max} + T_{\min}}{2} - T_{\text{base}}, 0\right).$$

GDH:

$$\text{If} \quad T_{\text{max, i}} <= 5°\text{C} \rightarrow \text{GDH}_i = 0$$

$$\text{If} \quad T_{\text{max i}} > 5°\text{C and } T_{\text{min i}} > 5°\text{C} \rightarrow$$
$$\text{GDH}_i = 24 \times (T_{\text{min i}} - 5) + 12 \times (T_{\text{max i}} - T_{\text{min i}})$$

$$\text{If} \quad T_{\text{max i}} > 5°\text{C and } T_{\text{min i}} <= 5°\text{C} \rightarrow$$
$$\text{GDH}_i = 12 \times (T_{\text{max i}} - 5)^2/(T_{\text{max i}} - T_{\text{min i}})$$

```r
weather$GDD3<-ifelse(with(weather,((max+min)/2)-3)<0,0,with(weather,((max+min)/2)-3))
weather$GDD5<-ifelse(with(weather,((max+min)/2)-5)<0,0,with(weather,((max+min)/2)-5))
weather$GDD7<-ifelse(with(weather,((max+min)/2)-7)<0,0,with(weather,((max+min)/2)-7))
weather$GDD10<-ifelse(with(weather,((max+min)/2)-10)<0,0,with(weather,((max+min)/2)-10))
weather$GDH3<-ifelse(with(weather,max<=3),0,
                     ifelse(with(weather,max>3&min>3),with(weather,24*(min-3)+12*(max-min)),
                            with(weather,12*(max-3)^2/(max-min))))
weather$GDH5<-ifelse(with(weather,max<=5),0,
                     ifelse(with(weather,max>5&min>5),with(weather,24*(min-5)+12*(max-min)),
                            with(weather,12*(max-5)^2/(max-min))))
```

```r
weather$GDH7<-ifelse(with(weather,max<=7),0,
                     ifelse(with(weather,max>7&min>7),with(weather,24*(min-7)+12*(max-min)),
                            with(weather,12*(max-7)^2/(max-min))))
weather$GDH10<-ifelse(with(weather,max<=10),0,
                     ifelse(with(weather,max>10&min>10),with(weather,24*(min-10)+12*(max-min)),
                            with(weather,12*(max-10)^2/(max-min))))
pander(head(weather), split.table = 100, style = 'rmarkdown')
```

date	year	month	day	date_ok	mean	min	max	precipitation
1987-01-01	1987	1	1	01/01/1987	-11.25	-14.15	-8.5	0
1987-01-02	1987	1	2	02/01/1987	-11.5	-15.25	-7.65	0
1987-01-03	1987	1	3	03/01/1987	-10.25	-14.4	-7.9	0.3
1987-01-04	1987	1	4	04/01/1987	-13.35	-16.25	-9.2	1.1
1987-01-05	1987	1	5	05/01/1987	-5.95	-16.5	-2.5	0
1987-01-06	1987	1	6	06/01/1987	-11.85	-15.25	-4.25	2.8

GDD3	GDD5	GDD7	GDD10	GDH3	GDH5	GDH7	GDH10
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Calculate julian date as day with respect to vernal equinox

```r
weather<-merge(weather,unique(alldata[c(1,6)])) #Add column with date of vernal equinox
weather$vernal_time<-as.POSIXct(weather$vernal,format="%Y-%m-%d %H:%M:%S")
weather$vernal<-as.Date(substring(weather$vernal,1,10),format="%Y-%m-%d")
weather$date_julian<-as.numeric(with(weather,as.POSIXct(date)-vernal_time)/60/24)
```

Calculations weather by month

Calculate monthly means of temperature and montly sums of precipitation, GDD and GDH

```r
mean_weather1<-plyr::join_all(list(
    aggregate(mean ~ year+month, data=weather, FUN=mean), #Monthly means of mean daily temperature
    aggregate(min ~ year+month, data=weather, FUN=mean), #Monthly means of min daily temperature
    aggregate(max ~ year+month, data=weather, FUN=mean), #Monthly means of max daily temperature
    aggregate(precipitation ~ year+month, data= weather, FUN=sum),#Monthly sums of precipitation
    aggregate(GDD3 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDD3
    aggregate(GDD5 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDD5
    aggregate(GDD7 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDD7
    aggregate(GDD10 ~ year+month,data= weather, FUN=sum),         #Monthly sums of GDD10
    aggregate(GDH3 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDH3
    aggregate(GDH5 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDH5
    aggregate(GDH7 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDH7
    aggregate(GDH10 ~ year+month,data= weather, FUN=sum)),        #Monthly sums of GDH10
```

```
    by = NULL, type = "left", match = "all")
mean_weather2<-gather(mean_weather1, variable, value,mean,min,max,precipitation,
               GDD3,GDD5,GDD7,GDD10,GDH3,GDH5,GDH7,GDH10) %>%
               unite(var, variable, month) %>%
               spread(var, value) #Convert to wide format with monthly variables
pander(head(mean_weather1), split.table = 100, style = 'rmarkdown')
```

year	month	mean	min	max	precipitation	GDD3	GDD5	GDD7	GDD10
1987	1	-11.06	-14.89	-7.285	9.3	0	0	0	0
1988	1	0.9823	-0.2194	2.397	78	5.175	0.125	0	0
1989	1	3.556	0.8468	6.076	3.9	36.58	12.25	1.525	0
1990	1	1.848	-0.379	3.89	63.4	11.5	0	0	0
1991	1	0.2839	-2.135	2.829	50	1.025	0	0	0
1992	1	1.502	-1.344	4.556	33	25.68	6.475	1.925	0

GDH3	GDH5	GDH7	GDH10
1.581	0	0	0
155.5	18.19	0	0
1044	391.9	91.17	0.2146
394.8	57.66	0.8285	0
120.8	2.691	0	0
751.9	279.9	66.25	0.9524

Calculations FFD stats

Calculate mean, variance, duration, skewness and kurtosis of FFD and merge with previous data

```
mean_weather3<-merge(mean_weather2,
               as.data.frame(alldata %>% filter(!is.na(alldata$FFD)) %>%
                                         dplyr::select(year,FFD)  %>%
                                         dplyr::group_by(year) %>%
                                         dplyr::summarise(FFD_mean=mean(FFD),FFD_var=var(FFD),
                                         FFD_dur=range(FFD)[2]-range(FFD)[1],
                                         FFD_skew=skewness(FFD),FFD_kurt=kurtosis(FFD))
                                         ))
names(mean_weather3)
```

```
##   [1] "year"              "GDD10_1"           "GDD10_10"
##   [4] "GDD10_11"          "GDD10_12"          "GDD10_2"
##   [7] "GDD10_3"           "GDD10_4"           "GDD10_5"
##  [10] "GDD10_6"           "GDD10_7"           "GDD10_8"
##  [13] "GDD10_9"           "GDD3_1"            "GDD3_10"
##  [16] "GDD3_11"           "GDD3_12"           "GDD3_2"
##  [19] "GDD3_3"            "GDD3_4"            "GDD3_5"
##  [22] "GDD3_6"            "GDD3_7"            "GDD3_8"
##  [25] "GDD3_9"            "GDD5_1"            "GDD5_10"
##  [28] "GDD5_11"           "GDD5_12"           "GDD5_2"
##  [31] "GDD5_3"            "GDD5_4"            "GDD5_5"
##  [34] "GDD5_6"            "GDD5_7"            "GDD5_8"
##  [37] "GDD5_9"            "GDD7_1"            "GDD7_10"
```

```
##  [40] "GDD7_11"          "GDD7_12"          "GDD7_2"
##  [43] "GDD7_3"           "GDD7_4"           "GDD7_5"
##  [46] "GDD7_6"           "GDD7_7"           "GDD7_8"
##  [49] "GDD7_9"           "GDH10_1"          "GDH10_10"
##  [52] "GDH10_11"         "GDH10_12"         "GDH10_2"
##  [55] "GDH10_3"          "GDH10_4"          "GDH10_5"
##  [58] "GDH10_6"          "GDH10_7"          "GDH10_8"
##  [61] "GDH10_9"          "GDH3_1"           "GDH3_10"
##  [64] "GDH3_11"          "GDH3_12"          "GDH3_2"
##  [67] "GDH3_3"           "GDH3_4"           "GDH3_5"
##  [70] "GDH3_6"           "GDH3_7"           "GDH3_8"
##  [73] "GDH3_9"           "GDH5_1"           "GDH5_10"
##  [76] "GDH5_11"          "GDH5_12"          "GDH5_2"
##  [79] "GDH5_3"           "GDH5_4"           "GDH5_5"
##  [82] "GDH5_6"           "GDH5_7"           "GDH5_8"
##  [85] "GDH5_9"           "GDH7_1"           "GDH7_10"
##  [88] "GDH7_11"          "GDH7_12"          "GDH7_2"
##  [91] "GDH7_3"           "GDH7_4"           "GDH7_5"
##  [94] "GDH7_6"           "GDH7_7"           "GDH7_8"
##  [97] "GDH7_9"           "max_1"            "max_10"
## [100] "max_11"           "max_12"           "max_2"
## [103] "max_3"            "max_4"            "max_5"
## [106] "max_6"            "max_7"            "max_8"
## [109] "max_9"            "mean_1"           "mean_10"
## [112] "mean_11"          "mean_12"          "mean_2"
## [115] "mean_3"           "mean_4"           "mean_5"
## [118] "mean_6"           "mean_7"           "mean_8"
## [121] "mean_9"           "min_1"            "min_10"
## [124] "min_11"           "min_12"           "min_2"
## [127] "min_3"            "min_4"            "min_5"
## [130] "min_6"            "min_7"            "min_8"
## [133] "min_9"            "precipitation_1"  "precipitation_10"
## [136] "precipitation_11" "precipitation_12" "precipitation_2"
## [139] "precipitation_3"  "precipitation_4"  "precipitation_5"
## [142] "precipitation_6"  "precipitation_7"  "precipitation_8"
## [145] "precipitation_9"  "FFD_mean"         "FFD_var"
## [148] "FFD_dur"          "FFD_skew"         "FFD_kurt"
```

Calculations cumulated GDD/GDH

Sum of GDD/GDH until each date, starting from the start of the year

```
#From the start of the year
weather<-as.data.frame(weather %>%
         dplyr::group_by(year) %>%
         dplyr::mutate(cumGDD3=cumsum(x = GDD3),cumGDD5=cumsum(x = GDD5),
                cumGDD7=cumsum(x = GDD7),cumGDD10=cumsum(x = GDD10),
                cumGDH3=cumsum(x = GDH3),cumGDH5=cumsum(x = GDH5),
                cumGDH7=cumsum(x = GDH7),cumGDH10=cumsum(x = GDH10)))
```

Merge with previous data

```
weather$FFD<-weather$date_julian
alldata_weather<-merge(alldata, weather[c(1,6:17,21:29)], all.x=T,all.y=F)
```

Load new data with some missing values for weather manually substituted in OpenOffice Calc (merging by date of FFD did not work in cases where FFD was imputed, because that FFD did not correspond exactly to a "real" date - I merged it manually with the closest value)

```
alldata_weather_subs<-read.table("C:/Users/User/Dropbox/SU/Projects/lathyrus/data/clean/alldata_weather_
nrow(subset(alldata_weather_subs,is.na(mean)&!is.na(FFD))) #No rows with missing weather data
```

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

```
nrow(subset(alldata_weather_subs,n_fr>cum_n_fl)) #No cases where n_fruits>n_flowers --> fix again
```

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

Calculations proportion of plants that have started flowering at each FFD

```
#Number of plants flowering per year at each FFD
alldata_weather_subs$year<-as.factor(alldata_weather_subs$year)
alldata_agg<- aggregate(FFD~cumGDD3+cumGDD5+cumGDD7+cumGDD10+cumGDH3+cumGDH5+cumGDH7+cumGDH10+year,
                        data=alldata_weather_subs[c(1:3,35:42)],FUN=length)

#Cumulated number of plants flowering per year at each FFD
alldata_agg<-as.data.frame(alldata_agg %>%
                dplyr::group_by(year) %>%
                dplyr::mutate(n_cum_FFD = cumsum(x = FFD)))

#Calculate proportion of plants flowering per year at each FFD
max_nflowering<-aggregate(n_cum_FFD ~year, data=alldata_agg,FUN=max)
max_nflowering$max_nflowering<-max_nflowering$n_cum_FFD
max_nflowering$n_cum_FFD<-NULL

alldata_agg<-merge(alldata_agg,max_nflowering)
alldata_agg$prop_fl<-alldata_agg$n_cum_FFD/alldata_agg$max_nflowering
```

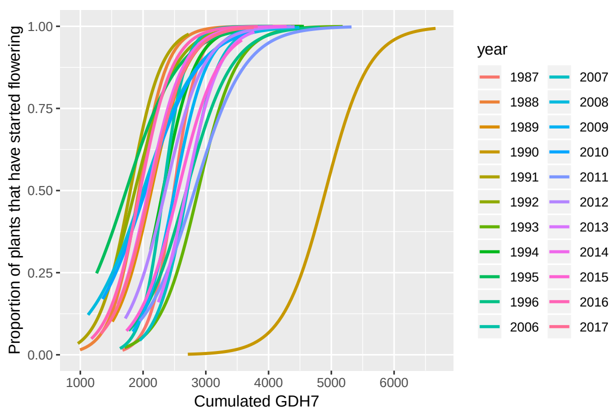
Models of proportion of plants that have started flowering against cumulated GDD/GDH

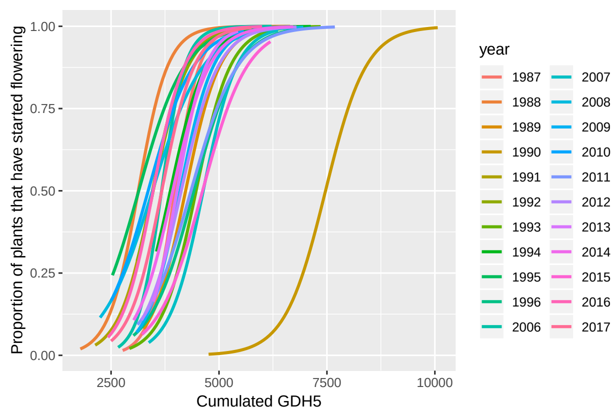
```
#Fit univariate binomial GLMs of prop_fl against each predictor
models1<-lapply(names(alldata_agg)[2:9],
         function(x) {glm(substitute(prop_fl ~ scale(i), list(i = as.name(x))),
                          family=binomial, data = alldata_agg)})

models1_summary<-lapply(X = models1, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models1_summary<-models1_summary[c(1:2,5,7)]
names(models1_summary)<-c("variable","Estimate","P","sig")
models1_summary<-subset(models1_summary,!variable=="(Intercept)")
models1_summary<-cbind(models1_summary,sapply(lapply(X = models1, FUN = NagelkerkeR2), "[[", 2))
names(models1_summary)[5]<-"Rsquare"
kable(arrange(subset(models1_summary,sig=="*"|sig=="**"|sig=="***"),desc(Rsquare)))
```

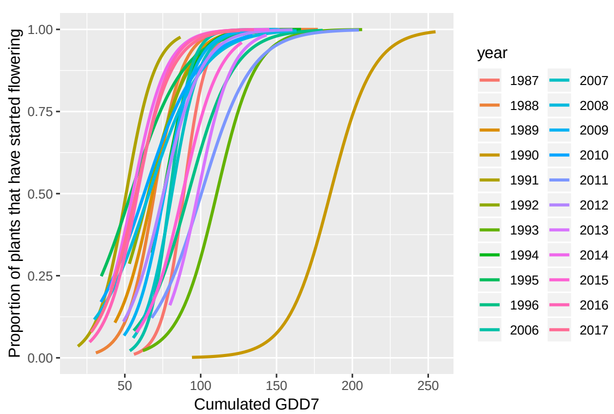
variable	Estimate	P	sig	Rsquare
scale(cumGDH7)	1.997160	<0.001	***	0.7368036
scale(cumGDH5)	1.936327	<0.001	***	0.7303357
scale(cumGDD5)	1.936957	<0.001	***	0.7296362
scale(cumGDD7)	1.912560	<0.001	***	0.7024659
scale(cumGDD3)	1.767286	<0.001	***	0.6746137
scale(cumGDH10)	1.843080	<0.001	***	0.6521309
scale(cumGDH3)	1.700881	<0.001	***	0.6504500
scale(cumGDD10)	1.578339	<0.001	***	0.5489817

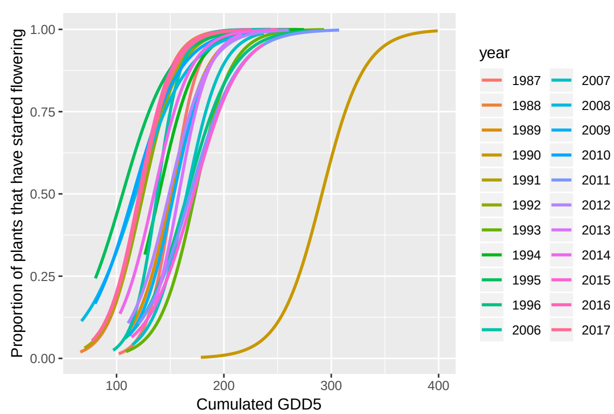
Plots of the best models

Some plots of the best models of proportion of plants that have started flowering against cumulated GDD/GDH



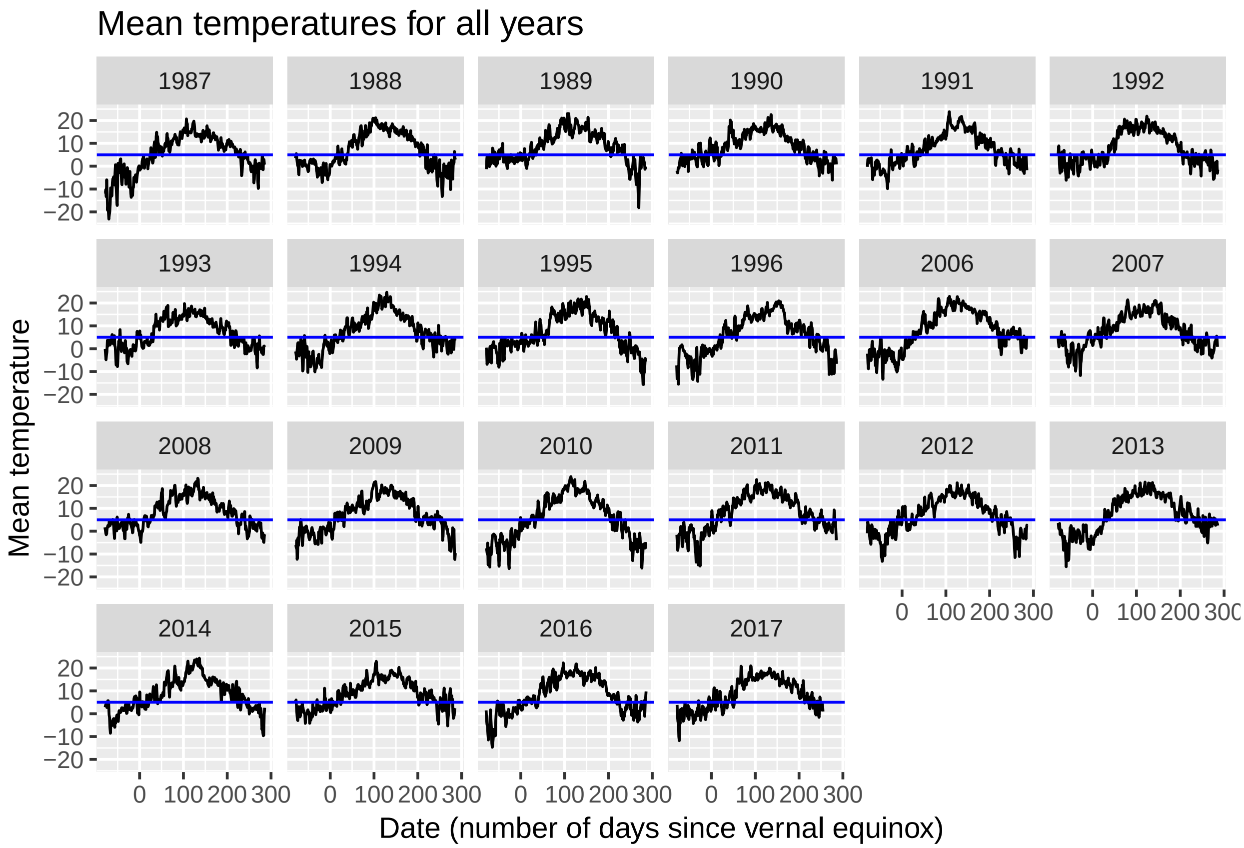


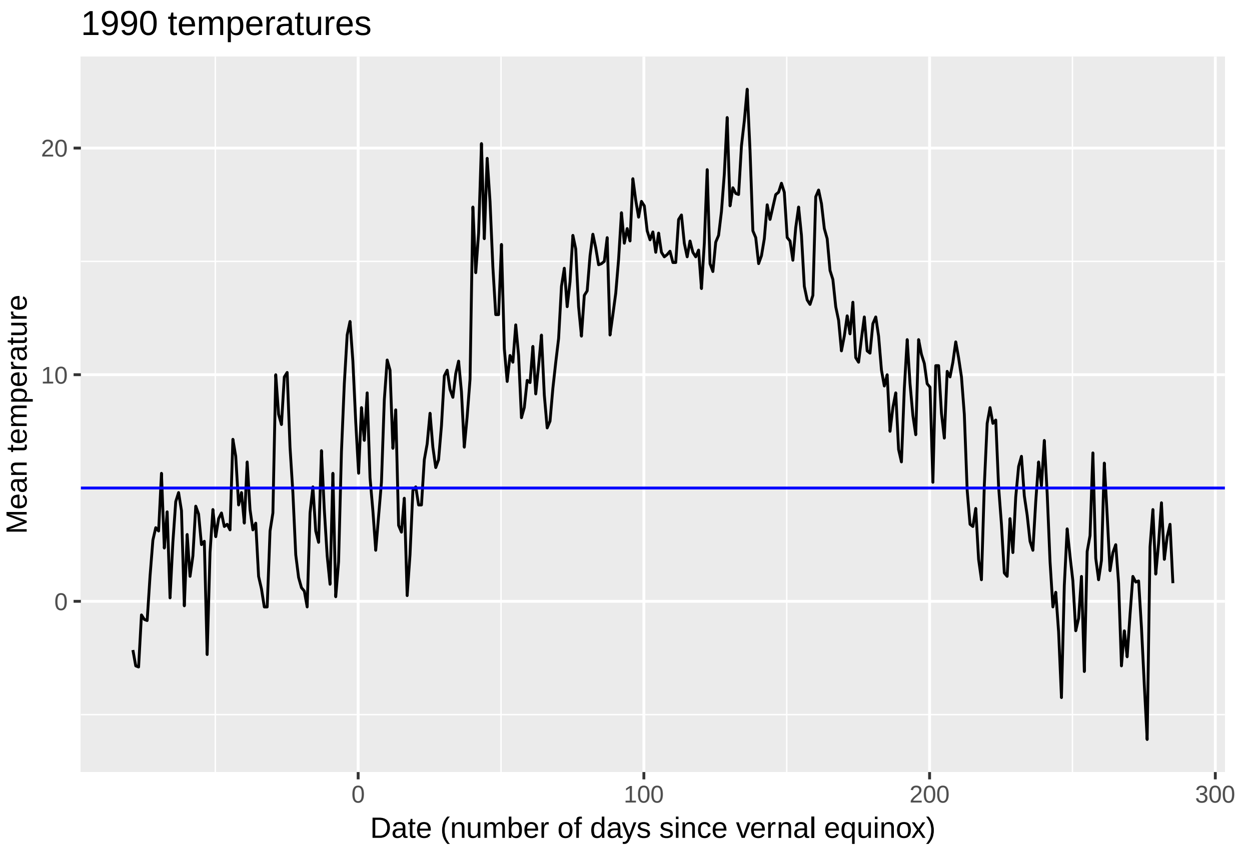


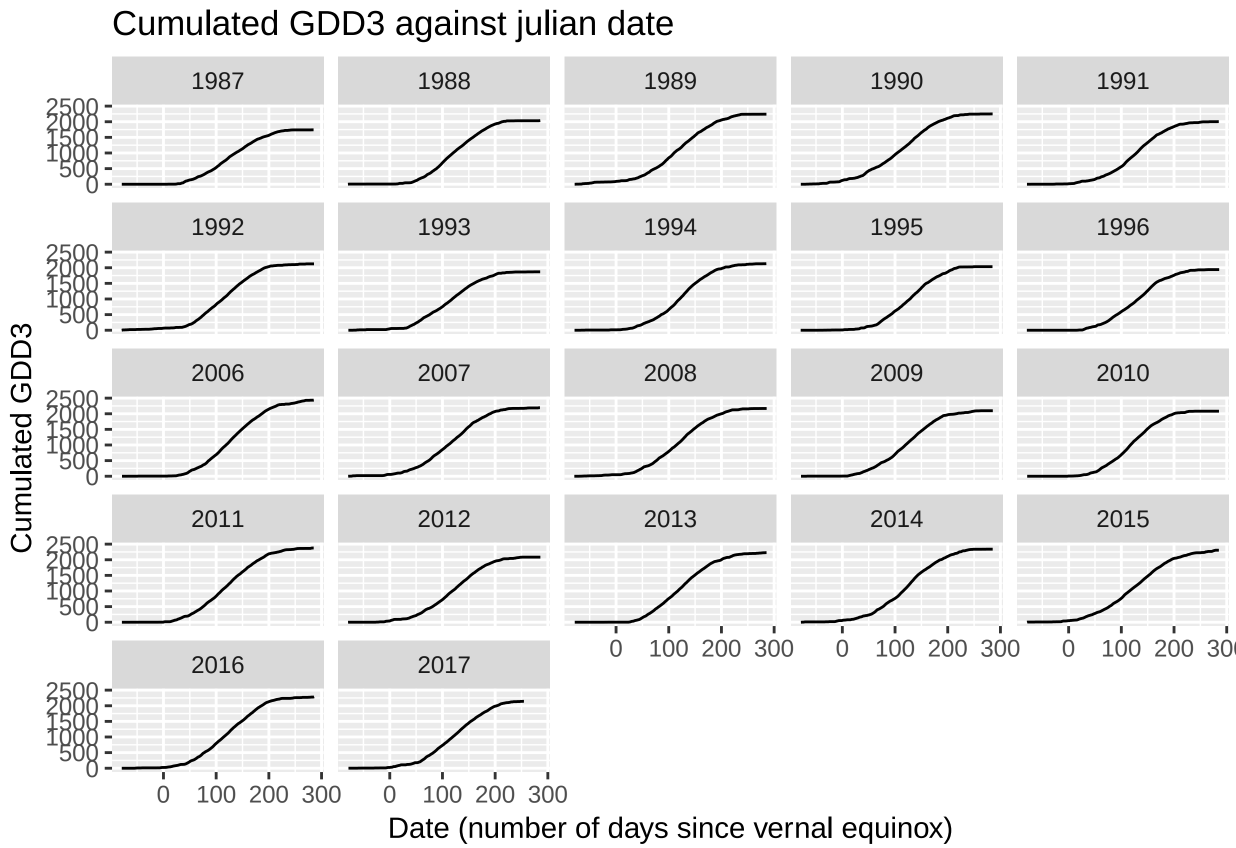


Plots for year 1990

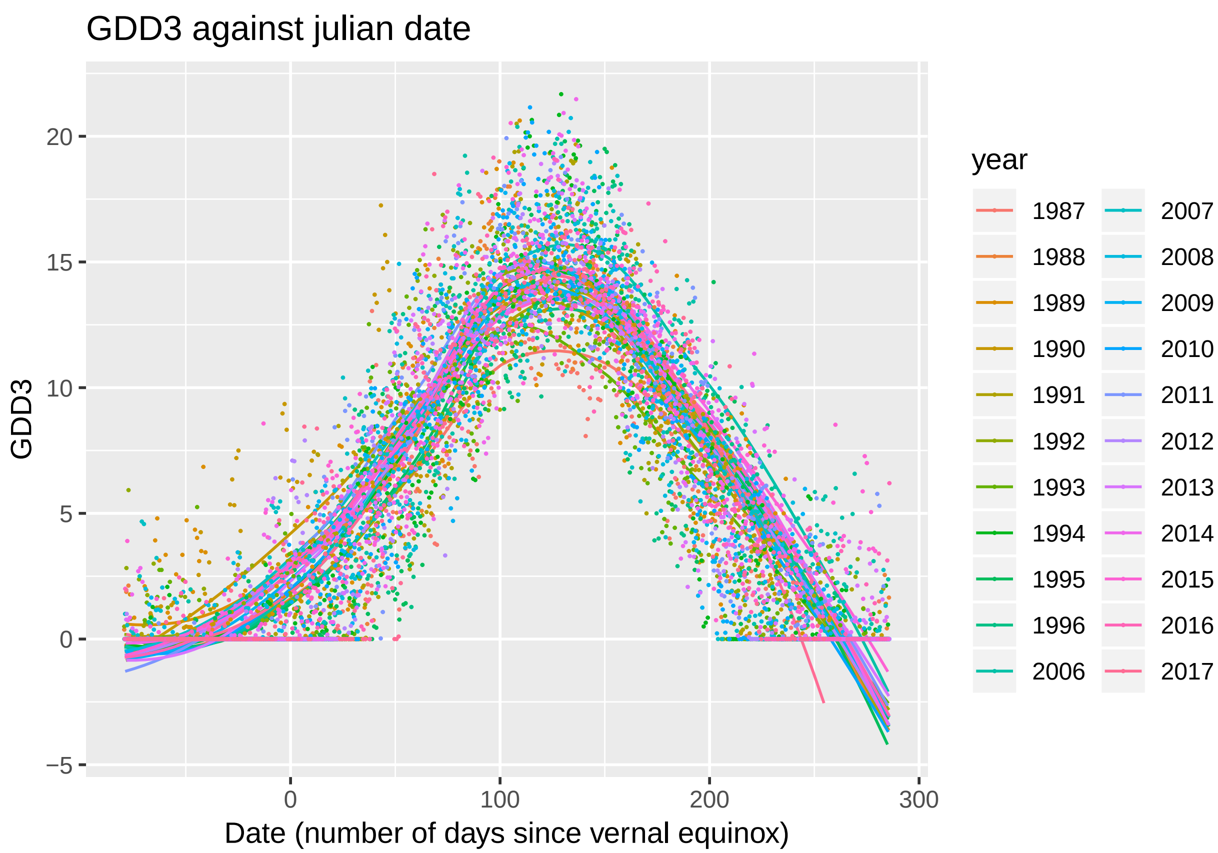
Year 1990 shows high values of GDD/GDH
Some plots to look at these high values

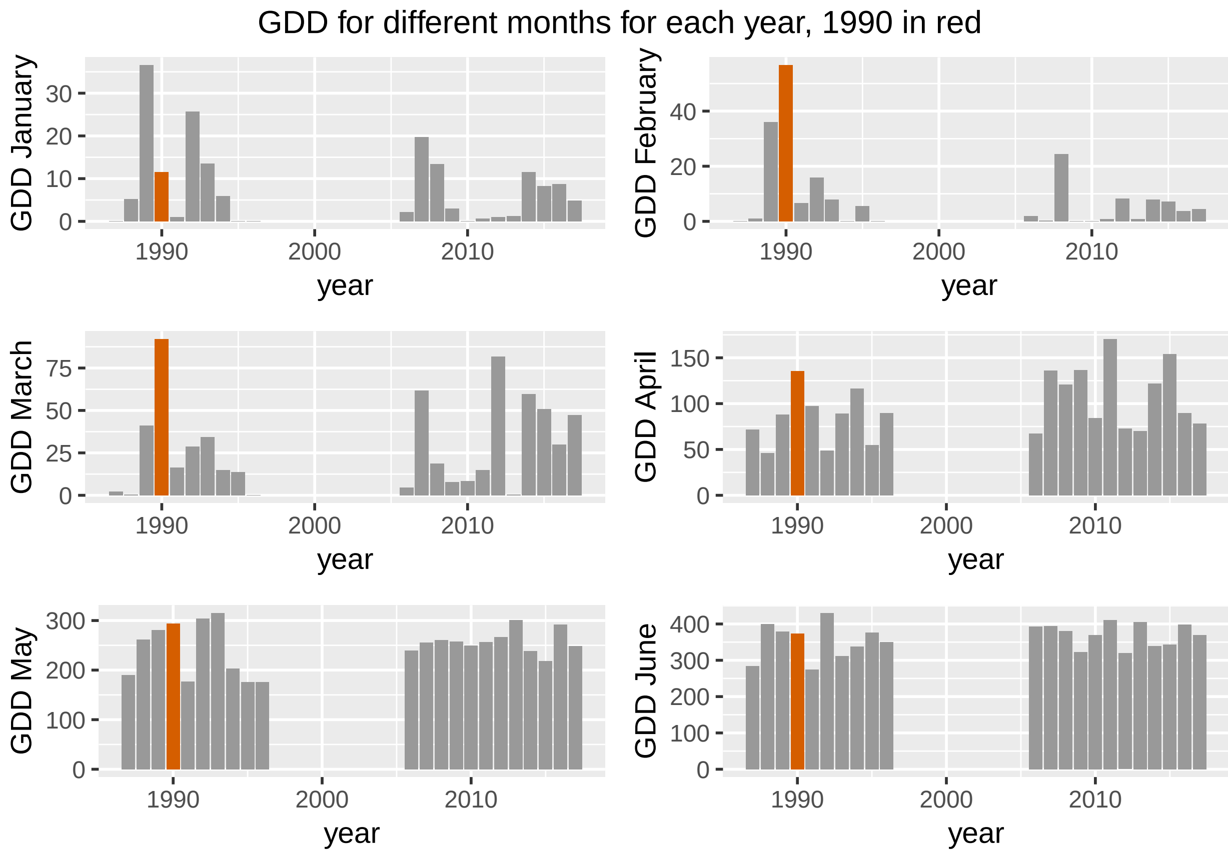

Mean temperatures for all years
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
Mean temperature
20
10
0
−10
−20
0
100
200
300
Date (number of days since vernal equinox)


1990 temperatures
Mean temperature
20
10
0
0
100
200
300
Date (number of days since vernal equinox)



Cumulated GDD3 against julian date
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
0
500
1000
1500
2000
2500
0
100
200
300
Cumulated GDD3
Date (number of days since vernal equinox)


GDD3 against julian date
20
15
10
5
0
−5
GDD3
0
100
200
300
Date (number of days since vernal equinox)
year
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017



GDD are very high in February and March 1990 - many days above the base temperature in these months.

Select data for analyses paper

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

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

Calculation of relative fitness and standardized traits

Relativization and standardization was done within each year.

```
data_sel<-data.frame(
  data_sel %>%
  group_by(year) %>%
  mutate(n_intact_seeds_rel=n_intact_seeds/mean(n_intact_seeds)) %>% #Relative fitness
```

```
  mutate(FFD_std=(FFD-mean(FFD))/sd(FFD)) %>%                    #Standardized FFD
  mutate(n_fl_std=(n_fl-mean(n_fl))/sd(n_fl)))                   #Standardized n_fl
```

Calculation of position and duration of flowering season

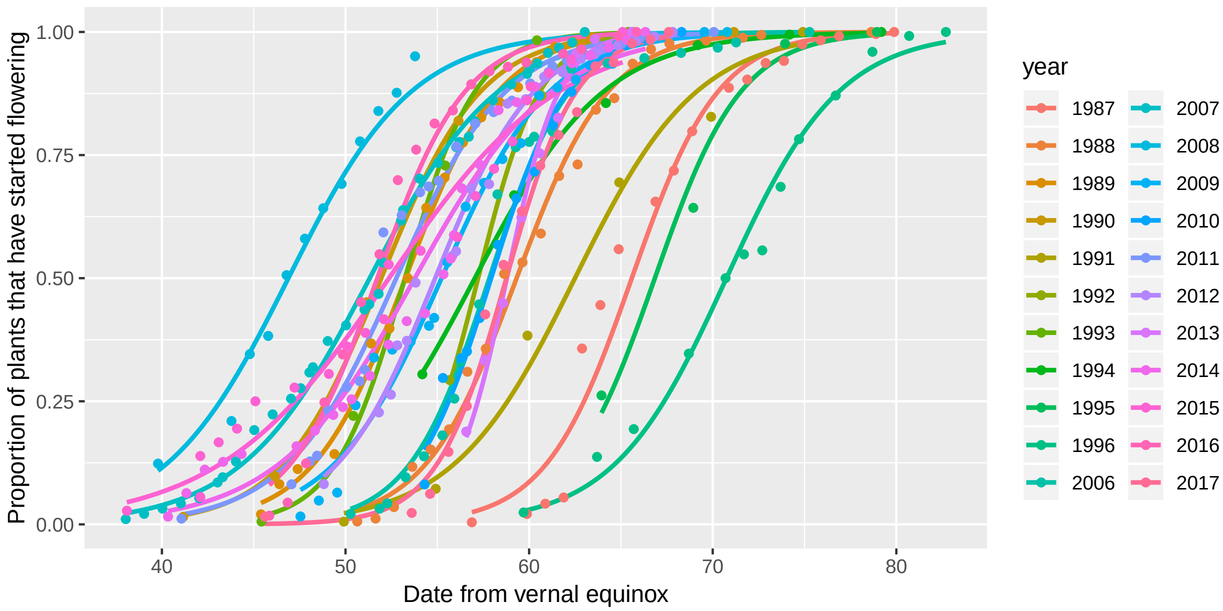
Calculate proportion of plants flowering per year at each date

```
propfl<-as.data.frame(aggregate(id~FFD+year,data=alldata_weather_subs[c(1:3)],FUN=length) %>%
        group_by(year) %>%
        mutate(n_cum_FFD = cumsum(x = id))) #Cumulated n plants fl per yr at each FFD

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

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

Models proportion of plants flowering per year against date

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

```
## # A tibble: 44 x 6
## # Groups:   year [22]
##    year  term        estimate std.error statistic   p.value
##    <fct> <chr>          <dbl>     <dbl>     <dbl>     <dbl>
##  1 1987  (Intercept)  -27.7      0.808      -34.3 9.89e-258
##  2 1987  FFD            0.422    0.0122      34.5 1.74e-260
##  3 1988  (Intercept)  -23.6      0.748      -31.5 2.16e-218
##  4 1988  FFD            0.398    0.0126      31.7 4.45e-220
##  5 1989  (Intercept)  -20.9      0.937      -22.3 2.19e-110
##  6 1989  FFD            0.393    0.0174      22.6 5.79e-113
##  7 1990  (Intercept)  -19.1      1.30       -14.7 1.00e- 48
##  8 1990  FFD            0.367    0.0249      14.8 2.71e- 49
##  9 1991  (Intercept)  -18.7      1.06       -17.7 5.22e- 70
## 10 1991  FFD            0.299    0.0169      17.8 1.64e- 70
## # ... with 34 more rows
```



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

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

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

```
##   year  date_10  date_90
## 1 1987 60.38876 70.79705
## 2 1988 53.79735 64.83949
## 3 1989 47.67251 58.86038
## 4 1990 45.95380 57.93525
## 5 1991 55.15323 69.84053
## 6 1992 55.78171 60.94629
```

Calculate other metrics of the flowering season and merge

```
fl_pos_dur<-merge(as.data.frame(alldata %>% filter(!is.na(alldata$FFD)) %>%
            dplyr::select(year,FFD)  %>%
            dplyr::group_by(year) %>%
            dplyr::summarise(FFD_mean=mean(FFD),FFD_first=min(FFD), FFD_last=max(FFD),
                             FFD_var=var(FFD),FFD_dur=range(FFD)[2]-range(FFD)[1],
                             FFD_skew=skewness(FFD),FFD_kurt=kurtosis(FFD))),dates_fl)
fl_pos_dur$days_90_10<-with(fl_pos_dur,date_90-date_10) # Another measure of duration
head(fl_pos_dur)
```

```
##   year FFD_mean FFD_first FFD_last   FFD_var FFD_dur  FFD_skew FFD_kurt
## 1 1987 66.25589  56.88194 79.88194 16.699234      23 0.8572106 3.190485
## 2 1988 59.90789  50.63889 78.63889 20.244857      28 0.5740425 3.870109
## 3 1989 53.85571  45.39653 65.39653 18.807595      20 0.1890922 2.724365
## 4 1990 54.46244  41.15417 71.15417 26.093643      30 0.2424504 3.493801
```

```
## 5 1991 64.99514  49.91181 74.91181 36.445531      25 0.2544649 2.228982
## 6 1992 59.85048  55.66944 65.66944  9.975637      10 0.1406066 2.434292
##    date_10  date_90 days_90_10
## 1 60.38876 70.79705  10.408284
## 2 53.79735 64.83949  11.042139
## 3 47.67251 58.86038  11.187872
## 4 45.95380 57.93525  11.981455
## 5 55.15323 69.84053  14.687303
## 6 55.78171 60.94629   5.164579
```

```
mean_weather4<-merge(mean_weather3,fl_pos_dur[c(1,3:4,9:11)])
data_sel<-merge(data_sel,fl_pos_dur)
```

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  131
## 5  1991  165
## 6  1992  116
## 7  1993  171
## 8  1994  166
## 9  1995   35
## 10 1996  124
## 11 2006   87
## 12 2007   93
## 13 2008   80
## 14 2009   59
## 15 2010   74
## 16 2011   85
## 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	-0.504	0.161	-3.129	0.002	*
10	1991	FFD_std	-0.600	0.078	-7.646	0.000	*
12	1992	FFD_std	-0.438	0.183	-2.391	0.018	*
14	1993	FFD_std	-0.448	0.131	-3.410	0.001	*
16	1994	FFD_std	-0.558	0.176	-3.177	0.002	*
18	1995	FFD_std	-0.487	0.218	-2.236	0.032	*
20	1996	FFD_std	-0.373	0.106	-3.512	0.001	*
22	2006	FFD_std	-0.423	0.133	-3.177	0.002	*
24	2007	FFD_std	-0.411	0.111	-3.712	0.000	*
26	2008	FFD_std	-0.500	0.120	-4.149	0.000	*
28	2009	FFD_std	-0.213	0.276	-0.772	0.444	
30	2010	FFD_std	-0.492	0.164	-3.008	0.004	*
32	2011	FFD_std	-0.696	0.196	-3.545	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 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,"*","")
seldiffs_FFD_q$estimate<-ifelse(seldiffs_FFD_q$term=="I(FFD_std^2)",2*(seldiffs_FFD_q$estimate),
                                seldiffs_FFD_q$estimate)
seldiffs_FFD_q$std.error<-ifelse(seldiffs_FFD_q$term=="I(FFD_std^2)",2*(seldiffs_FFD_q$std.error),
                                seldiffs_FFD_q$std.error)
#Double Quadratic regression coefficients and standard errors
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)	-0.053	0.153	-0.348	0.728	
6	1988	I(FFD_std^2)	-0.060	0.134	-0.444	0.658	
9	1989	I(FFD_std^2)	0.133	0.198	0.673	0.502	
12	1990	I(FFD_std^2)	0.233	0.212	1.099	0.274	
15	1991	I(FFD_std^2)	0.132	0.140	0.945	0.346	
18	1992	I(FFD_std^2)	0.029	0.311	0.092	0.927	
21	1993	I(FFD_std^2)	0.040	0.217	0.184	0.854	
24	1994	I(FFD_std^2)	0.287	0.285	1.009	0.315	
27	1995	I(FFD_std^2)	0.307	0.357	0.860	0.396	
30	1996	I(FFD_std^2)	-0.178	0.179	-0.997	0.321	
33	2006	I(FFD_std^2)	0.169	0.147	1.151	0.253	
36	2007	I(FFD_std^2)	0.190	0.192	0.991	0.324	

	year	term	estimate	std.error	statistic	p.value	sig
39	2008	I(FFD_std^2)	0.321	0.126	2.549	0.013	*
42	2009	I(FFD_std^2)	-0.438	0.495	-0.884	0.381	
45	2010	I(FFD_std^2)	0.283	0.284	0.994	0.324	
48	2011	I(FFD_std^2)	0.370	0.262	1.416	0.161	
51	2012	I(FFD_std^2)	1.119	0.275	4.063	0.000	*
54	2013	I(FFD_std^2)	0.006	0.605	0.011	0.992	
57	2014	I(FFD_std^2)	0.355	0.286	1.241	0.219	
60	2015	I(FFD_std^2)	-0.846	0.475	-1.783	0.084	
63	2016	I(FFD_std^2)	0.015	0.136	0.112	0.911	
66	2017	I(FFD_std^2)	-0.249	0.501	-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	0.678	0.156	4.346	0.000	*
10	1991	n_fl_std	0.667	0.075	8.877	0.000	*
12	1992	n_fl_std	0.114	0.187	0.606	0.546	
14	1993	n_fl_std	0.435	0.132	3.307	0.001	*
16	1994	n_fl_std	0.487	0.177	2.751	0.007	*
18	1995	n_fl_std	0.420	0.222	1.892	0.067	
20	1996	n_fl_std	0.642	0.095	6.750	0.000	*
22	2006	n_fl_std	0.776	0.113	6.866	0.000	*
24	2007	n_fl_std	0.275	0.115	2.387	0.019	*
26	2008	n_fl_std	0.760	0.102	7.479	0.000	*
28	2009	n_fl_std	0.319	0.274	1.165	0.249	
30	2010	n_fl_std	0.280	0.170	1.644	0.104	
32	2011	n_fl_std	0.914	0.185	4.933	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,"*","")
seldiffs_nfl_q$estimate<-ifelse(seldiffs_nfl_q$term=="I(nfl_std^2)",2*(seldiffs_nfl_q$estimate),
                                seldiffs_nfl_q$estimate)
seldiffs_nfl_q$std.error<-ifelse(seldiffs_nfl_q$term=="I(nflD_std^2)",2*(seldiffs_nfl_q$std.error),
                                seldiffs_nfl_q$std.error)
#Double Quadratic regression coefficients and standard errors
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)	-0.229	0.070	-3.292	0.001	*
15	1991	I(n_fl_std^2)	-0.013	0.060	-0.210	0.834	
18	1992	I(n_fl_std^2)	-0.261	0.106	-2.455	0.016	*
21	1993	I(n_fl_std^2)	-0.132	0.086	-1.532	0.127	
24	1994	I(n_fl_std^2)	-0.166	0.094	-1.769	0.079	
27	1995	I(n_fl_std^2)	-0.191	0.115	-1.664	0.106	
30	1996	I(n_fl_std^2)	-0.078	0.070	-1.121	0.264	
33	2006	I(n_fl_std^2)	-0.095	0.042	-2.260	0.026	*
36	2007	I(n_fl_std^2)	-0.132	0.053	-2.489	0.015	*
39	2008	I(n_fl_std^2)	-0.101	0.057	-1.760	0.082	
42	2009	I(n_fl_std^2)	-0.258	0.125	-2.058	0.044	*
45	2010	I(n_fl_std^2)	-0.300	0.109	-2.740	0.008	*
48	2011	I(n_fl_std^2)	0.036	0.131	0.276	0.783	
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)])
seldiffs$estimate<-round(seldiffs$estimate,3)
seldiffs$std.error<-round(seldiffs$std.error,3)
kable(seldiffs,digits=3) # Table S1
```

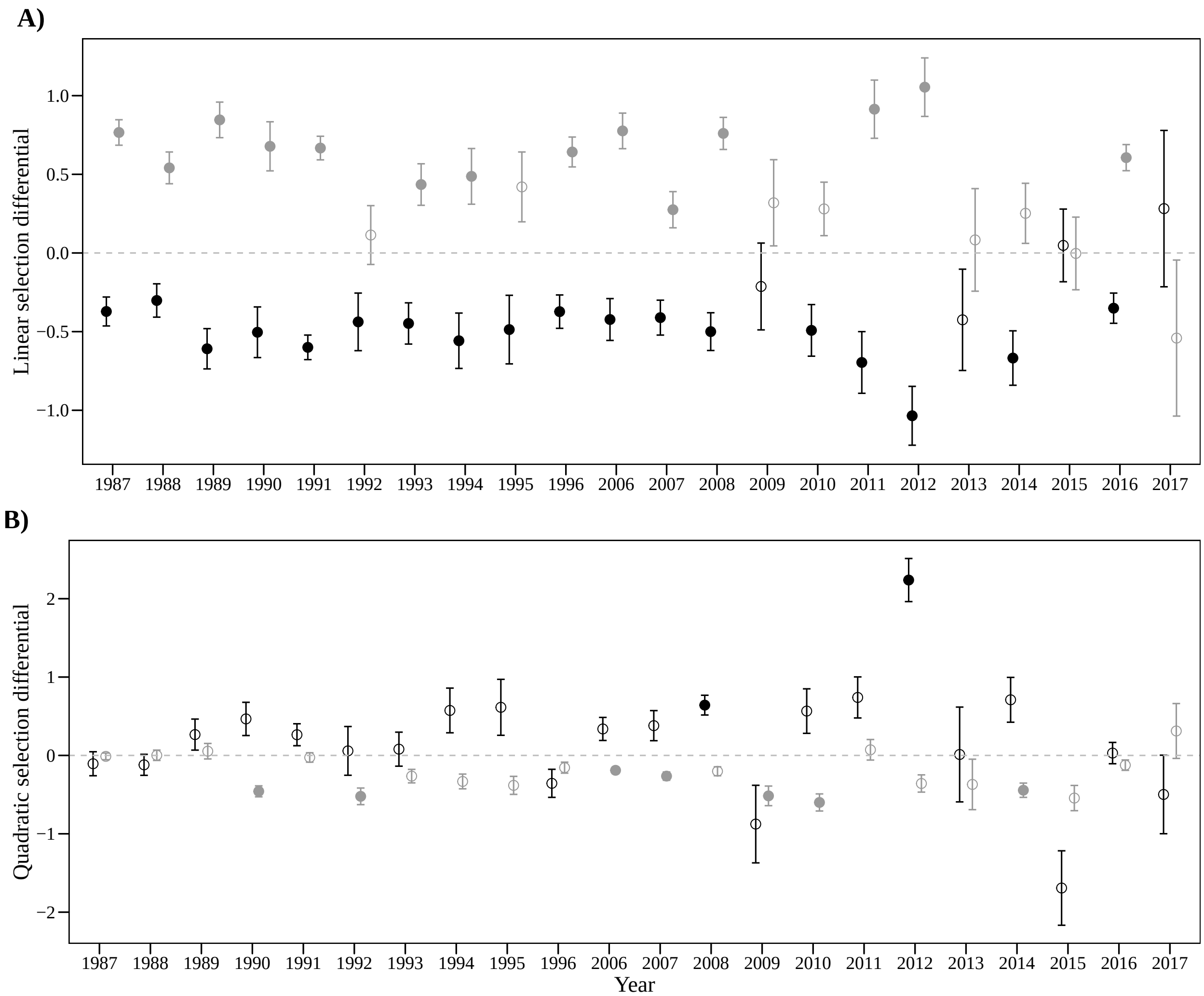
	year	term	estimate	std.error	sig
2	1987	FFD_std	-0.372	0.092	*
4	1988	FFD_std	-0.302	0.106	*
6	1989	FFD_std	-0.609	0.128	*

	year	term	estimate	std.error	sig
8	1990	FFD_std	-0.504	0.161	*
10	1991	FFD_std	-0.600	0.078	*
12	1992	FFD_std	-0.438	0.183	*
14	1993	FFD_std	-0.448	0.131	*
16	1994	FFD_std	-0.558	0.176	*
18	1995	FFD_std	-0.487	0.218	*
20	1996	FFD_std	-0.373	0.106	*
22	2006	FFD_std	-0.423	0.133	*
24	2007	FFD_std	-0.411	0.111	*
26	2008	FFD_std	-0.500	0.120	*
28	2009	FFD_std	-0.213	0.276	
30	2010	FFD_std	-0.492	0.164	*
32	2011	FFD_std	-0.696	0.196	*
34	2012	FFD_std	-1.035	0.187	*
36	2013	FFD_std	-0.425	0.322	
38	2014	FFD_std	-0.668	0.173	*
40	2015	FFD_std	0.048	0.231	
42	2016	FFD_std	-0.351	0.096	*
44	2017	FFD_std	0.282	0.497	
3	1987	I(FFD_std^2)	-0.053	0.153	
61	1988	I(FFD_std^2)	-0.060	0.134	
9	1989	I(FFD_std^2)	0.133	0.198	
121	1990	I(FFD_std^2)	0.233	0.212	
15	1991	I(FFD_std^2)	0.132	0.140	
181	1992	I(FFD_std^2)	0.029	0.311	
21	1993	I(FFD_std^2)	0.040	0.217	
241	1994	I(FFD_std^2)	0.287	0.285	
27	1995	I(FFD_std^2)	0.307	0.357	
301	1996	I(FFD_std^2)	-0.178	0.179	
33	2006	I(FFD_std^2)	0.169	0.147	
361	2007	I(FFD_std^2)	0.190	0.192	
39	2008	I(FFD_std^2)	0.321	0.126	*
421	2009	I(FFD_std^2)	-0.438	0.495	
45	2010	I(FFD_std^2)	0.283	0.284	
48	2011	I(FFD_std^2)	0.370	0.262	
51	2012	I(FFD_std^2)	1.119	0.275	*
54	2013	I(FFD_std^2)	0.006	0.605	
57	2014	I(FFD_std^2)	0.355	0.286	
60	2015	I(FFD_std^2)	-0.846	0.475	
63	2016	I(FFD_std^2)	0.015	0.136	
66	2017	I(FFD_std^2)	-0.249	0.501	
23	1987	n_fl_std	0.766	0.081	*
41	1988	n_fl_std	0.541	0.101	*
62	1989	n_fl_std	0.846	0.113	*
81	1990	n_fl_std	0.678	0.156	*
101	1991	n_fl_std	0.667	0.075	*
122	1992	n_fl_std	0.114	0.187	
141	1993	n_fl_std	0.435	0.132	*
161	1994	n_fl_std	0.487	0.177	*
182	1995	n_fl_std	0.420	0.222	
201	1996	n_fl_std	0.642	0.095	*
221	2006	n_fl_std	0.776	0.113	*

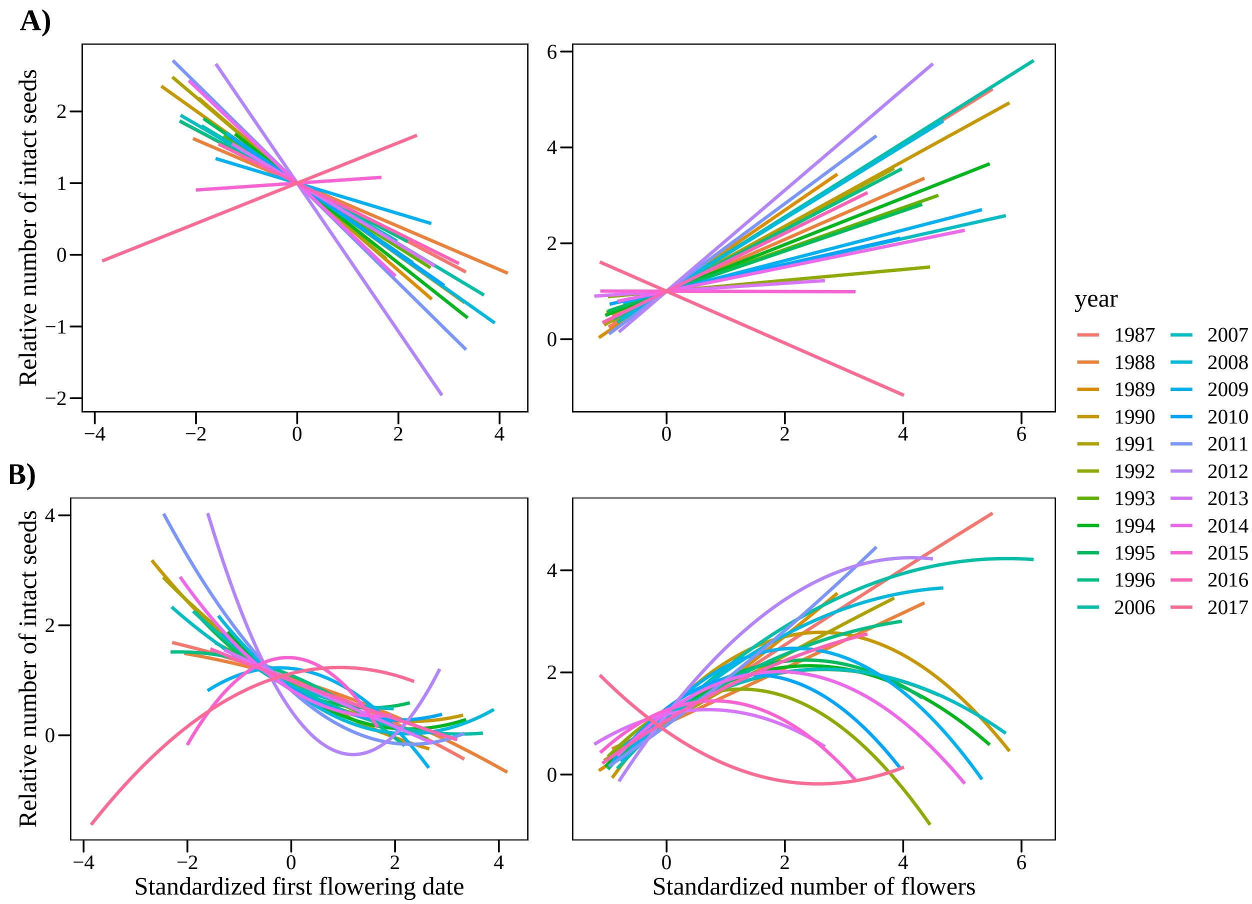
	year	term	estimate	std.error	sig
242	2007	n_fl_std	0.275	0.115	*
261	2008	n_fl_std	0.760	0.102	*
281	2009	n_fl_std	0.319	0.274	
302	2010	n_fl_std	0.280	0.170	
321	2011	n_fl_std	0.914	0.185	*
341	2012	n_fl_std	1.054	0.186	*
362	2013	n_fl_std	0.083	0.326	
381	2014	n_fl_std	0.252	0.191	
401	2015	n_fl_std	-0.003	0.231	
422	2016	n_fl_std	0.606	0.083	*
441	2017	n_fl_std	-0.541	0.496	
31	1987	I(n_fl_std^2)	-0.006	0.043	
64	1988	I(n_fl_std^2)	0.001	0.066	
91	1989	I(n_fl_std^2)	0.027	0.099	
123	1990	I(n_fl_std^2)	-0.229	0.070	*
151	1991	I(n_fl_std^2)	-0.013	0.060	
183	1992	I(n_fl_std^2)	-0.261	0.106	*
211	1993	I(n_fl_std^2)	-0.132	0.086	
243	1994	I(n_fl_std^2)	-0.166	0.094	
271	1995	I(n_fl_std^2)	-0.191	0.115	
303	1996	I(n_fl_std^2)	-0.078	0.070	
331	2006	I(n_fl_std^2)	-0.095	0.042	*
363	2007	I(n_fl_std^2)	-0.132	0.053	*
391	2008	I(n_fl_std^2)	-0.101	0.057	
423	2009	I(n_fl_std^2)	-0.258	0.125	*
451	2010	I(n_fl_std^2)	-0.300	0.109	*
481	2011	I(n_fl_std^2)	0.036	0.131	
511	2012	I(n_fl_std^2)	-0.179	0.110	
541	2013	I(n_fl_std^2)	-0.185	0.322	
571	2014	I(n_fl_std^2)	-0.222	0.091	*
601	2015	I(n_fl_std^2)	-0.272	0.161	
631	2016	I(n_fl_std^2)	-0.062	0.066	
661	2017	I(n_fl_std^2)	0.156	0.350	

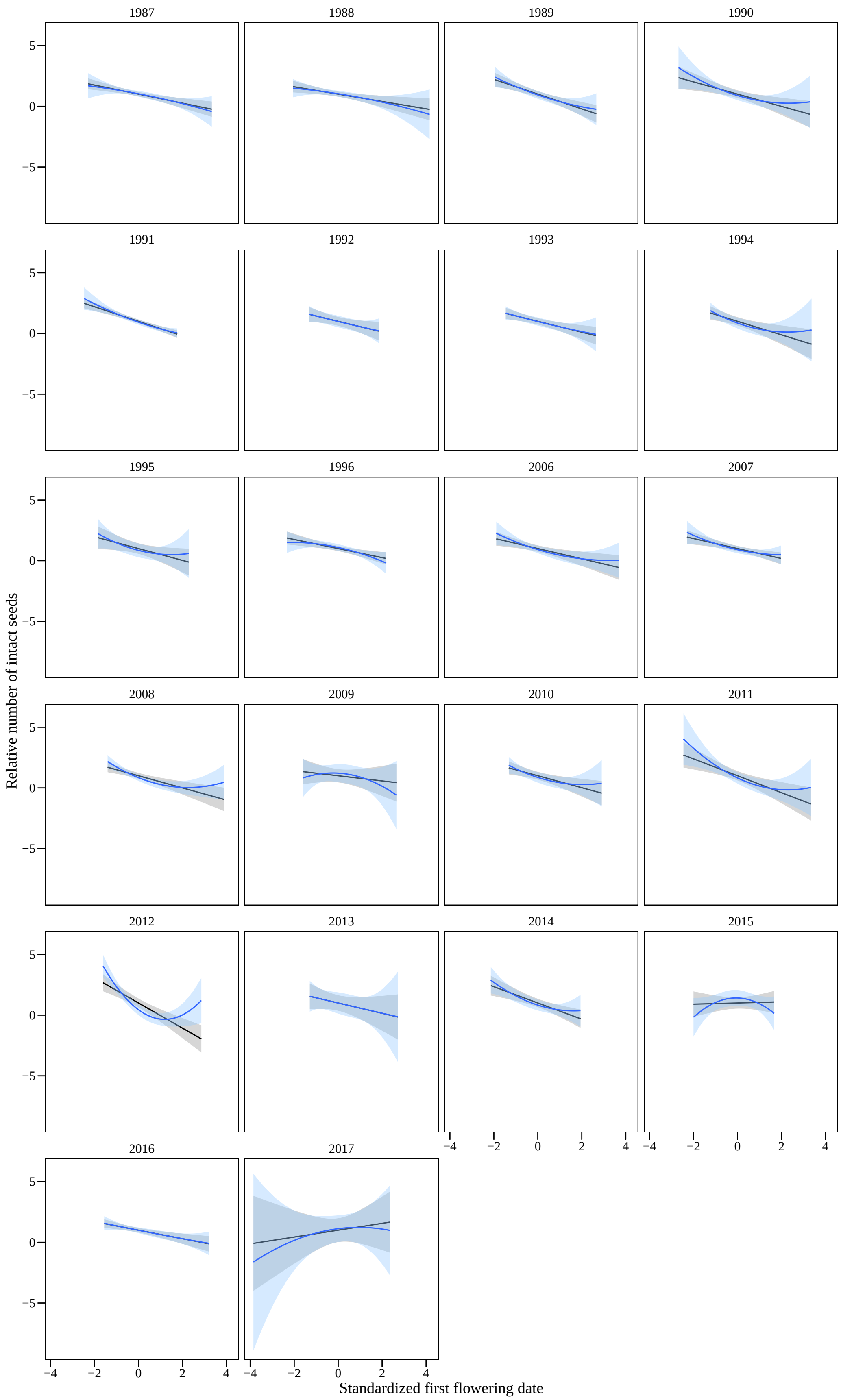
```
write.table(seldiffs,file="seldiffs.txt",sep="\t")
```

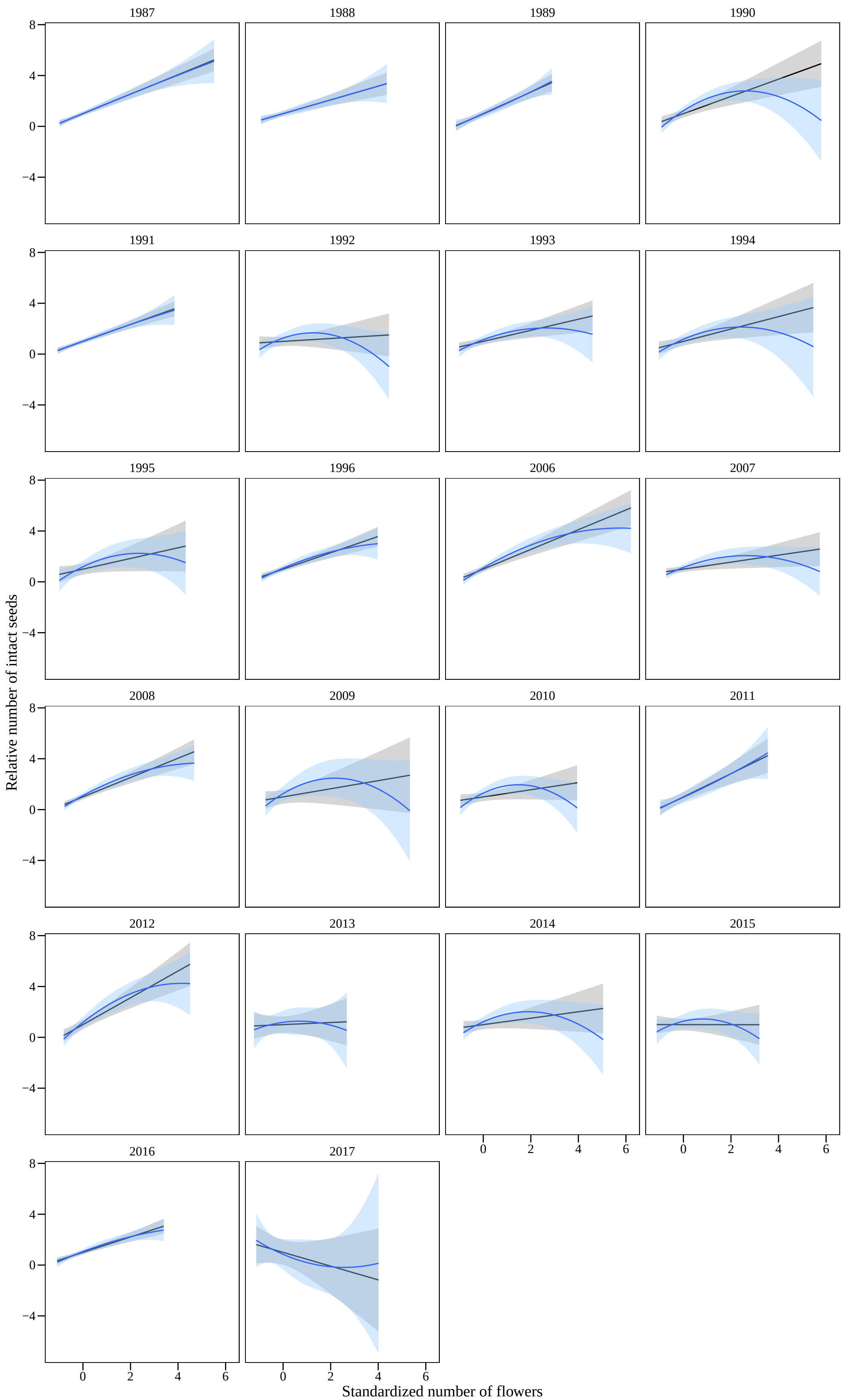
Plots



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
2
1
0
−1
−2
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
5
0
−5
−4
−2
0
2
4
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	-0.276	0.169	-1.631	0.105	
14	1991	FFD_std	-0.321	0.089	-3.597	0.000	*
17	1992	FFD_std	-0.463	0.199	-2.323	0.022	*
20	1993	FFD_std	-0.321	0.144	-2.236	0.027	*
23	1994	FFD_std	-0.439	0.188	-2.340	0.020	*
26	1995	FFD_std	-0.371	0.248	-1.497	0.144	
29	1996	FFD_std	-0.170	0.101	-1.684	0.095	
32	2006	FFD_std	-0.210	0.117	-1.796	0.076	
35	2007	FFD_std	-0.368	0.131	-2.816	0.006	*
38	2008	FFD_std	-0.201	0.112	-1.796	0.076	
41	2009	FFD_std	-0.052	0.332	-0.158	0.875	
44	2010	FFD_std	-0.478	0.195	-2.459	0.016	*
47	2011	FFD_std	-0.292	0.218	-1.338	0.185	
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 1991,1992,1993,1994,2007,2010,2012,2014
```

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)	-0.009	0.129	-0.072	0.942	
27	1991	I(FFD_std^2)	0.056	0.087	0.646	0.519	
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)	0.105	0.127	0.827	0.410	
45	1994	I(FFD_std^2)	0.099	0.160	0.617	0.538	
51	1995	I(FFD_std^2)	0.100	0.280	0.358	0.723	
57	1996	I(FFD_std^2)	-0.049	0.093	-0.529	0.598	
63	2006	I(FFD_std^2)	0.131	0.085	1.549	0.125	
69	2007	I(FFD_std^2)	0.248	0.147	1.681	0.096	
75	2008	I(FFD_std^2)	0.070	0.066	1.049	0.297	
81	2009	I(FFD_std^2)	0.031	0.301	0.102	0.919	
87	2010	I(FFD_std^2)	0.196	0.165	1.183	0.241	
93	2011	I(FFD_std^2)	0.050	0.168	0.300	0.765	
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	-0.285	0.287	-0.996	0.321	
30	1991	FFD_std:n_fl_std	0.183	0.172	1.063	0.289	
36	1992	FFD_std:n_fl_std	0.172	0.252	0.681	0.497	
42	1993	FFD_std:n_fl_std	0.222	0.196	1.132	0.259	
48	1994	FFD_std:n_fl_std	-0.084	0.225	-0.374	0.709	
54	1995	FFD_std:n_fl_std	-0.070	0.496	-0.141	0.889	
60	1996	FFD_std:n_fl_std	-0.006	0.139	-0.041	0.967	
66	2006	FFD_std:n_fl_std	0.340	0.255	1.333	0.186	
72	2007	FFD_std:n_fl_std	0.394	0.263	1.498	0.138	
78	2008	FFD_std:n_fl_std	-0.096	0.245	-0.391	0.697	
84	2009	FFD_std:n_fl_std	2.395	0.883	2.713	0.009	*
90	2010	FFD_std:n_fl_std	0.379	0.358	1.061	0.293	
96	2011	FFD_std:n_fl_std	-0.313	0.503	-0.623	0.535	
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 1988,2009 and 2016
```

All selection gradients

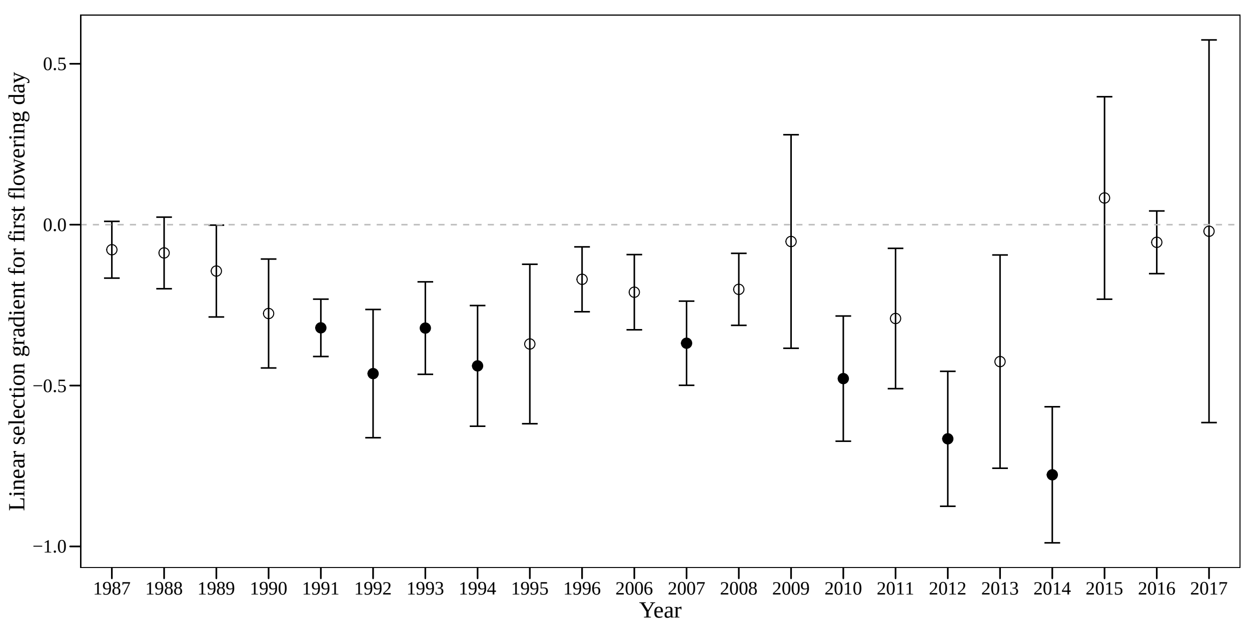
```r
selgrads<-rbind(subset(selgrads_FFD,term=="FFD_std")[c(1:4,7)],
                subset(selgrads_FFD_q,term=="I(FFD_std^2)")[c(1:4,7)],
                subset(selgrads_FFD_q,term=="FFD_std:n_fl_std")[c(1:4,7)])
selgrads$estimate<-round(selgrads$estimate,3)
selgrads$std.error<-round(selgrads$std.error,3)
kable(selgrads,digits=3) # Table S2
```

	year	term	estimate	std.error	sig
2	1987	FFD_std	-0.078	0.088	
5	1988	FFD_std	-0.088	0.111	
8	1989	FFD_std	-0.144	0.143	
11	1990	FFD_std	-0.276	0.169	
14	1991	FFD_std	-0.321	0.089	*
17	1992	FFD_std	-0.463	0.199	*
20	1993	FFD_std	-0.321	0.144	*
23	1994	FFD_std	-0.439	0.188	*
26	1995	FFD_std	-0.371	0.248	
29	1996	FFD_std	-0.170	0.101	
32	2006	FFD_std	-0.210	0.117	
35	2007	FFD_std	-0.368	0.131	*
38	2008	FFD_std	-0.201	0.112	
41	2009	FFD_std	-0.052	0.332	
44	2010	FFD_std	-0.478	0.195	*
47	2011	FFD_std	-0.292	0.218	
50	2012	FFD_std	-0.665	0.210	*
53	2013	FFD_std	-0.426	0.331	
56	2014	FFD_std	-0.777	0.211	*
59	2015	FFD_std	0.083	0.315	
62	2016	FFD_std	-0.055	0.097	
65	2017	FFD_std	-0.020	0.595	
3	1987	I(FFD_std^2)	-0.071	0.085	
9	1988	I(FFD_std^2)	0.091	0.075	
15	1989	I(FFD_std^2)	0.035	0.134	
21	1990	I(FFD_std^2)	-0.009	0.129	
27	1991	I(FFD_std^2)	0.056	0.087	
33	1992	I(FFD_std^2)	0.096	0.184	
39	1993	I(FFD_std^2)	0.105	0.127	
45	1994	I(FFD_std^2)	0.099	0.160	
51	1995	I(FFD_std^2)	0.100	0.280	
57	1996	I(FFD_std^2)	-0.049	0.093	
63	2006	I(FFD_std^2)	0.131	0.085	
69	2007	I(FFD_std^2)	0.248	0.147	
75	2008	I(FFD_std^2)	0.070	0.066	
81	2009	I(FFD_std^2)	0.031	0.301	
87	2010	I(FFD_std^2)	0.196	0.165	
93	2011	I(FFD_std^2)	0.050	0.168	
99	2012	I(FFD_std^2)	0.370	0.187	
105	2013	I(FFD_std^2)	0.178	0.362	
111	2014	I(FFD_std^2)	0.340	0.207	
117	2015	I(FFD_std^2)	-0.975	0.364	*
123	2016	I(FFD_std^2)	0.005	0.076	
129	2017	I(FFD_std^2)	-0.206	0.406	
6	1987	FFD_std:n_fl_std	0.010	0.180	

	year	term	estimate	std.error	sig
12	1988	FFD_std:n_fl_std	0.578	0.179	*
18	1989	FFD_std:n_fl_std	0.061	0.225	
24	1990	FFD_std:n_fl_std	-0.285	0.287	
30	1991	FFD_std:n_fl_std	0.183	0.172	
36	1992	FFD_std:n_fl_std	0.172	0.252	
42	1993	FFD_std:n_fl_std	0.222	0.196	
48	1994	FFD_std:n_fl_std	-0.084	0.225	
54	1995	FFD_std:n_fl_std	-0.070	0.496	
60	1996	FFD_std:n_fl_std	-0.006	0.139	
66	2006	FFD_std:n_fl_std	0.340	0.255	
72	2007	FFD_std:n_fl_std	0.394	0.263	
78	2008	FFD_std:n_fl_std	-0.096	0.245	
84	2009	FFD_std:n_fl_std	2.395	0.883	*
90	2010	FFD_std:n_fl_std	0.379	0.358	
96	2011	FFD_std:n_fl_std	-0.313	0.503	
102	2012	FFD_std:n_fl_std	-0.335	0.430	
108	2013	FFD_std:n_fl_std	0.455	0.449	
114	2014	FFD_std:n_fl_std	0.315	0.351	
120	2015	FFD_std:n_fl_std	-1.041	0.555	
126	2016	FFD_std:n_fl_std	0.500	0.189	*
132	2017	FFD_std:n_fl_std	-0.006	0.759	

```
write.table(selgrads,file="selgrads.txt",sep="\t")
```

Plots



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

Merge data

```
selgrads_FFD_values<-subset(selgrads_FFD,term=="FFD_std")[c(1,3)]
selgrads_FFD_values$selgradFFD<-selgrads_FFD_values$estimate
selgrads_FFD_values$estimate<-NULL
data_sel_agg<-merge(mean_weather4,selgrads_FFD_values)
data_sel_agg$year<-as.factor(data_sel_agg$year)
data_sel<-merge(data_sel,data_sel_agg[c(1:145,156)],by="year")
```

Results 1: Among-year variation and trends

Trends

Trends in climate

```
with(summarySE(data_sel, measurevar="GDD5_3", groupvars=c("year")),tidy(lm(GDD5_3~as.integer(year)))) #
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)         6.81      6.73      1.01    0.324
## 2 as.integer(year)    0.381     0.513     0.744   0.466
```

```
with(summarySE(data_sel, measurevar="GDD5_4", groupvars=c("year")),tidy(lm(GDD5_4~as.integer(year)))) #
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)        43.8      11.4        3.85 0.00100
## 2 as.integer(year)    0.990     0.868      1.14 0.267
```

```
with(summarySE(data_sel, measurevar="GDD5_5", groupvars=c("year")),tidy(lm(GDD5_5~as.integer(year)))) #
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic      p.value
##   <chr>               <dbl>     <dbl>     <dbl>        <dbl>
## 1 (Intercept)       176.        18.9      9.31  0.0000000104
## 2 as.integer(year)    0.952      1.44     0.662 0.516
```

```
with(summarySE(data_sel, measurevar="max_3", groupvars=c("year")),tidy(lm(max_3~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)         3.51      1.15       3.04 0.00650
## 2 as.integer(year)    0.130     0.0879     1.47 0.156
```

```
with(summarySE(data_sel, measurevar="max_4", groupvars=c("year")),tidy(lm(max_4~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)         9.08      0.755     12.0  1.31e-10
## 2 as.integer(year)    0.106     0.0575     1.84 8.04e- 2
```

```
with(summarySE(data_sel, measurevar="max_5", groupvars=c("year")),tidy(lm(max_5~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic  p.value
##   <chr>                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)        15.4       0.780     19.7   1.38e-14
## 2 as.integer(year)    0.0335    0.0594     0.565 5.79e- 1
```

```
with(summarySE(data_sel, measurevar="mean_3", groupvars=c("year")),tidy(lm(mean_3~as.integer(year)))) #
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)         0.572     1.18       0.485   0.633
## 2 as.integer(year)    0.0815    0.0898     0.907   0.375
```

```
with(summarySE(data_sel, measurevar="mean_4", groupvars=c("year")),tidy(lm(mean_4~as.integer(year)))) #
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic      p.value
##   <chr>                <dbl>     <dbl>     <dbl>        <dbl>
## 1 (Intercept)         4.88      0.590       8.27 0.0000000689
## 2 as.integer(year)    0.0667    0.0449      1.49 0.153
```

```
with(summarySE(data_sel, measurevar="mean_5", groupvars=c("year")),tidy(lm(mean_5~as.integer(year)))) #
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic  p.value
##   <chr>                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)        10.5       0.637     16.4   4.38e-13
## 2 as.integer(year)    0.0265    0.0485     0.545 5.91e- 1
```

```
with(summarySE(data_sel, measurevar="min_3", groupvars=c("year")),tidy(lm(min_3~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)        -2.08      1.28      -1.63    0.119
## 2 as.integer(year)    0.0471    0.0973     0.484   0.634
```

```
with(summarySE(data_sel, measurevar="min_4", groupvars=c("year")),tidy(lm(min_4~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)         1.40      0.458      3.07  0.00609
## 2 as.integer(year)    0.0208    0.0349     0.595 0.558
```

```
with(summarySE(data_sel, measurevar="min_5", groupvars=c("year")),tidy(lm(min_5~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic  p.value
##   <chr>                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)         5.97      0.493     12.1   1.15e-10
## 2 as.integer(year)    0.0236    0.0375     0.629 5.37e- 1
```

```
with(summarySE(data_sel, measurevar="precipitation_1", groupvars=c("year")),tidy(lm(precipitation_1~as.
```

```
## # A tibble: 2 x 5
```

```
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)        35.2      12.2        2.88 0.00921
## 2 as.integer(year)    0.940     0.929      1.01 0.323
```

```
with(summarySE(data_sel, measurevar="precipitation_2", groupvars=c("year")),tidy(lm(precipitation_2~as.i
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)        31.3       7.46      4.20  0.000444
## 2 as.integer(year)    0.381     0.568     0.671 0.510
```

```
with(summarySE(data_sel, measurevar="precipitation_3", groupvars=c("year")),tidy(lm(precipitation_3~as.i
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)        26.3       7.95      3.31  0.00346
## 2 as.integer(year)    0.422     0.605     0.697 0.494
```

```
with(summarySE(data_sel, measurevar="precipitation_4", groupvars=c("year")),tidy(lm(precipitation_4~as.i
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)        24.6       9.57      2.57   0.0182
## 2 as.integer(year)    0.381     0.729     0.522  0.607
```

```
with(summarySE(data_sel, measurevar="precipitation_5", groupvars=c("year")),tidy(lm(precipitation_5~as.i
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)        27.5      10.2       2.69   0.0141
## 2 as.integer(year)    0.749     0.779     0.962  0.348
```

Trend in FFD

```
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)  593.      221.         2.69  0.0142
## 2 year_int      -0.267     0.110     -2.42  0.0251
```

Trend in fitness

```
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)  35.3     179.         0.197   0.846
## 2 year_int     -0.0151    0.0892    -0.169   0.867
```

Trend in selection gradients for FFD

```
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)  2.30      8.90        0.258   0.799
## 2 year_int    -0.00129  0.00445    -0.289   0.775
```

Proprtion of variation explained by year

FFD

```
with(data_sel,summary(lm(FFD~year))) #* Linear model, year=factor, Adjusted R-squared:  0.5906
```

```
##
## Call:
## lm(formula = FFD ~ year)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.7440  -3.3739  -0.3509   2.9507  22.8000
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  66.2559     0.3036 218.200  < 2e-16 ***
## year1988     -6.3480     0.4696 -13.518  < 2e-16 ***
## year1989    -12.4002     0.5622 -22.055  < 2e-16 ***
## year1990    -11.6666     0.5096 -22.893  < 2e-16 ***
## year1991     -1.7683     0.4745  -3.726 0.000199 ***
## year1992     -6.4054     0.5304 -12.075  < 2e-16 ***
## year1993    -10.4786     0.4696 -22.314  < 2e-16 ***
## year1994     -5.3851     0.4737 -11.368  < 2e-16 ***
## year1995      4.4001     0.8480   5.188  2.3e-07 ***
## year1996      5.2983     0.5188  10.212  < 2e-16 ***
## year2006     -7.5183     0.5869 -12.811  < 2e-16 ***
## year2007    -14.7632     0.5729 -25.771  < 2e-16 ***
## year2008    -18.2670     0.6054 -30.174  < 2e-16 ***
## year2009    -10.3873     0.6813 -15.247  < 2e-16 ***
## year2010     -7.5692     0.6235 -12.140  < 2e-16 ***
## year2011    -12.8932     0.5919 -21.782  < 2e-16 ***
## year2012    -10.5993     0.5401 -19.625  < 2e-16 ***
## year2013     -6.7810     0.6405 -10.587  < 2e-16 ***
## year2014    -12.2865     0.6637 -18.512  < 2e-16 ***
## year2015    -13.4203     0.8377 -16.020  < 2e-16 ***
## year2016    -13.8570     0.5384 -25.736  < 2e-16 ***
```

```
## year2017     -7.0210     0.5122 -13.709  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.684 on 2389 degrees of freedom
## Multiple R-squared:  0.5942, Adjusted R-squared:  0.5906
## F-statistic: 166.6 on 21 and 2389 DF,  p-value: < 2.2e-16
```

```
r.squaredGLMM(lmer(FFD~year+(1|id),data_sel))[,1] # with id as a random factor, R2 fixed = 0.58
```

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

```
##       R2m
## 0.5888106
```

Fitness

```
with(data_sel,summary(lm(n_intact_seeds~year))) #* Linear model, year=factor, Adjusted R-squared:  0.17
```

```
##
## Call:
## lm(formula = n_intact_seeds ~ year)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.562  -3.518  -1.302   1.698  88.274
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.7259     0.5401  14.304  < 2e-16 ***
## year1988     -3.5421     0.8353  -4.240 2.32e-05 ***
## year1989      0.9577     1.0001   0.958 0.338353
## year1990     -4.2080     0.9065  -4.642 3.64e-06 ***
## year1991     -0.4237     0.8441  -0.502 0.615746
## year1992     -6.5356     0.9436  -6.926 5.53e-12 ***
## year1993     -4.2252     0.8353  -5.058 4.56e-07 ***
## year1994     -5.6725     0.8426  -6.732 2.09e-11 ***
## year1995     -4.7339     1.5085  -3.138 0.001721 **
## year1996     -1.7421     0.9229  -1.888 0.059193 .
## year2006      1.4196     1.0440   1.360 0.174011
## year2007     -2.0435     1.0190  -2.005 0.045029 *
## year2008     10.8357     1.0769  10.062  < 2e-16 ***
## year2009     -6.3022     1.2119  -5.200 2.16e-07 ***
## year2010     -5.1741     1.1091  -4.665 3.25e-06 ***
## year2011     -6.7773     1.0529  -6.437 1.47e-10 ***
## year2012     -4.6805     0.9607  -4.872 1.18e-06 ***
## year2013     -7.2380     1.1393  -6.353 2.52e-10 ***
## year2014     -4.1862     1.1806  -3.546 0.000399 ***
## year2015     -1.0870     1.4901  -0.730 0.465767
## year2016      3.2049     0.9577   3.346 0.000832 ***
## year2017     -7.5673     0.9110  -8.306  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 8.333 on 2389 degrees of freedom
## Multiple R-squared:  0.1782, Adjusted R-squared:  0.1709
## F-statistic: 24.66 on 21 and 2389 DF,  p-value: < 2.2e-16
```

```
r.squaredGLMM(lmer(n_intact_seeds~year+(1|id),data_sel))[,1] # with id as a random factor, R2 fixed = 0
```

```
##       R2m
## 0.1829126
```

Selection

```
# Indirect selection
summary(lm(n_intact_seeds_rel ~ FFD_std,data = data_sel))$adj.r.squared
```

```
## [1] 0.04414804
```

```
summary(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:as.factor(year),data = data_sel))$adj.r.squared
```

```
## [1] 0.04958467
```

```
(0.04958467-0.04414804)*100 #Variation in indirect selection explained by year?
```

```
## [1] 0.543663
```

```
# Direct selection
summary(lm(n_intact_seeds_rel ~ FFD_std+n_fl_std,data = data_sel))$adj.r.squared
```

```
## [1] 0.071554
```

```
summary(lm(n_intact_seeds_rel ~ FFD_std+FFD_std:as.factor(year)+n_fl_std,data = data_sel))$adj.r.square
```

```
## [1] 0.07753877
```

```
(0.07753877-0.071554)*100 #Variation in direct selection explained by year?
```

```
## [1] 0.598477
```

```
# id as random???
```

Ranges and means

Mean daily temperature March

```
round(with(summarySE(subset(weather,month==3),measurevar="mean", groupvars=c("year","month")),range(mea
```

```
## [1] -3.8  5.4
```

```
round(with(summarySE(subset(weather,month==3),measurevar="mean", groupvars=c("year","month")),mean(mean
```

```
## [1] 1.5
```

Mean daily temperature April

```
round(with(summarySE(subset(weather,month==4),measurevar="mean", groupvars=c("year","month")),range(mea
```

```
## [1] 3.6 8.4
```

```
round(with(summarySE(subset(weather,month==4),measurevar="mean", groupvars=c("year","month")),mean(mean
```

```
## [1] 5.7
```

Mean daily temperature May

```
round(with(summarySE(subset(weather,month==5),measurevar="mean", groupvars=c("year","month")),range(mean
```

```
## [1]  8.3 13.0
```

```
round(with(summarySE(subset(weather,month==5),measurevar="mean", groupvars=c("year","month")),mean(mean)
```

```
## [1] 10.8
```

Mean FFD

```
round(with(summarySE(data_sel, measurevar="FFD", groupvars=c("year")),range(FFD)),1)
```

```
## [1] 48.0 71.6
```

```
round(with(summarySE(data_sel, measurevar="FFD", groupvars=c("year")),mean(FFD)),1)
```

```
## [1] 58.1
```

Mean fitness

```
round(with(summarySE(data_sel, measurevar="n_intact_seeds", groupvars=c("year")),range(n_intact_seeds))
```

```
## [1]  0.2 18.6
```

```
round(with(summarySE(data_sel, measurevar="n_intact_seeds", groupvars=c("year")),mean(n_intact_seeds)),
```

```
## [1] 5
```

Selection gradients for FFD

```
round(with(subset(selgrads_FFD,term=="FFD_std"),range(estimate)),1)
```

```
## [1] -0.8  0.1
```

```
round(with(subset(selgrads_FFD,term=="FFD_std"),mean(estimate)),1)
```

```
## [1] -0.3
```

Fig. 1 - REDO WITH ALL DATA

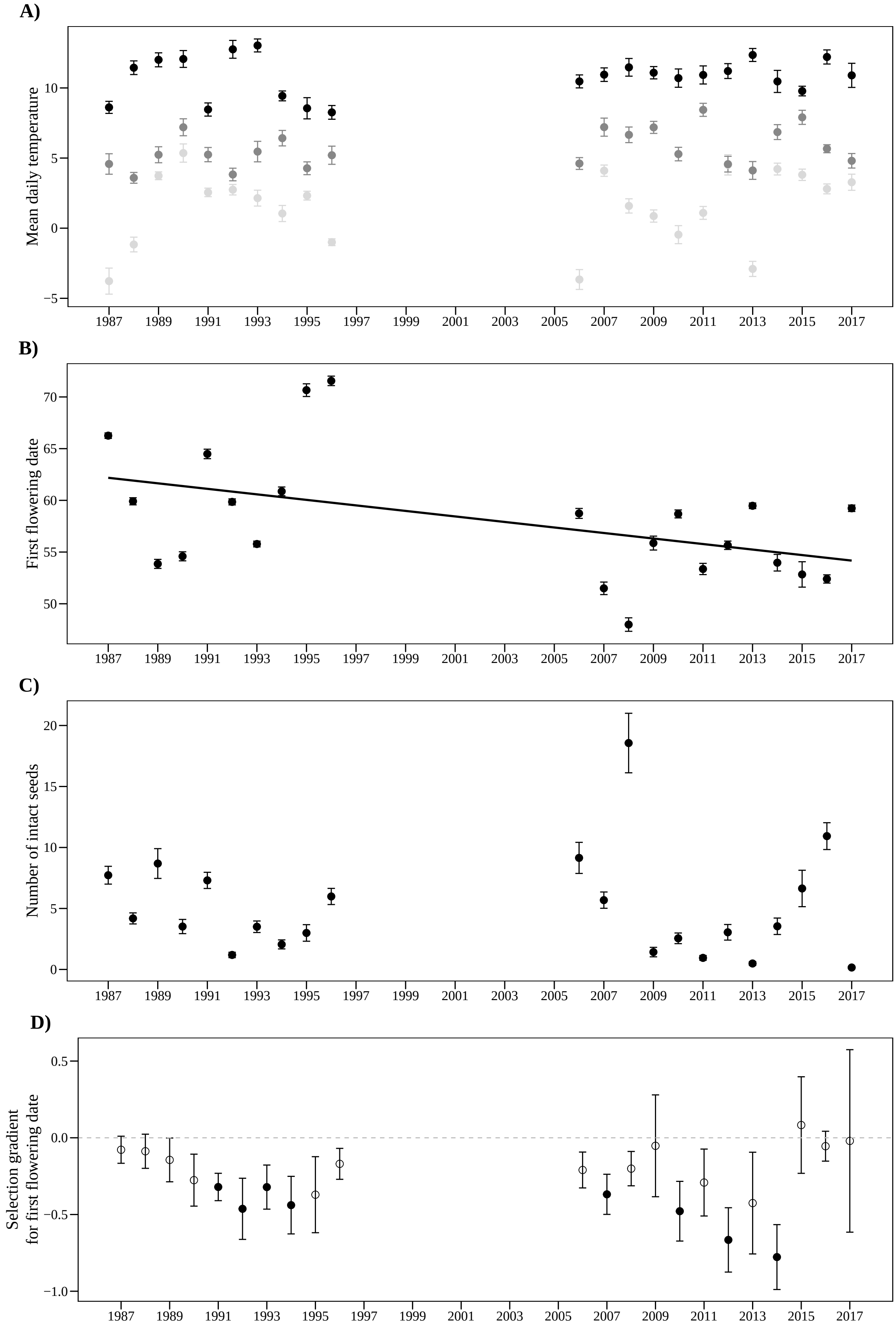
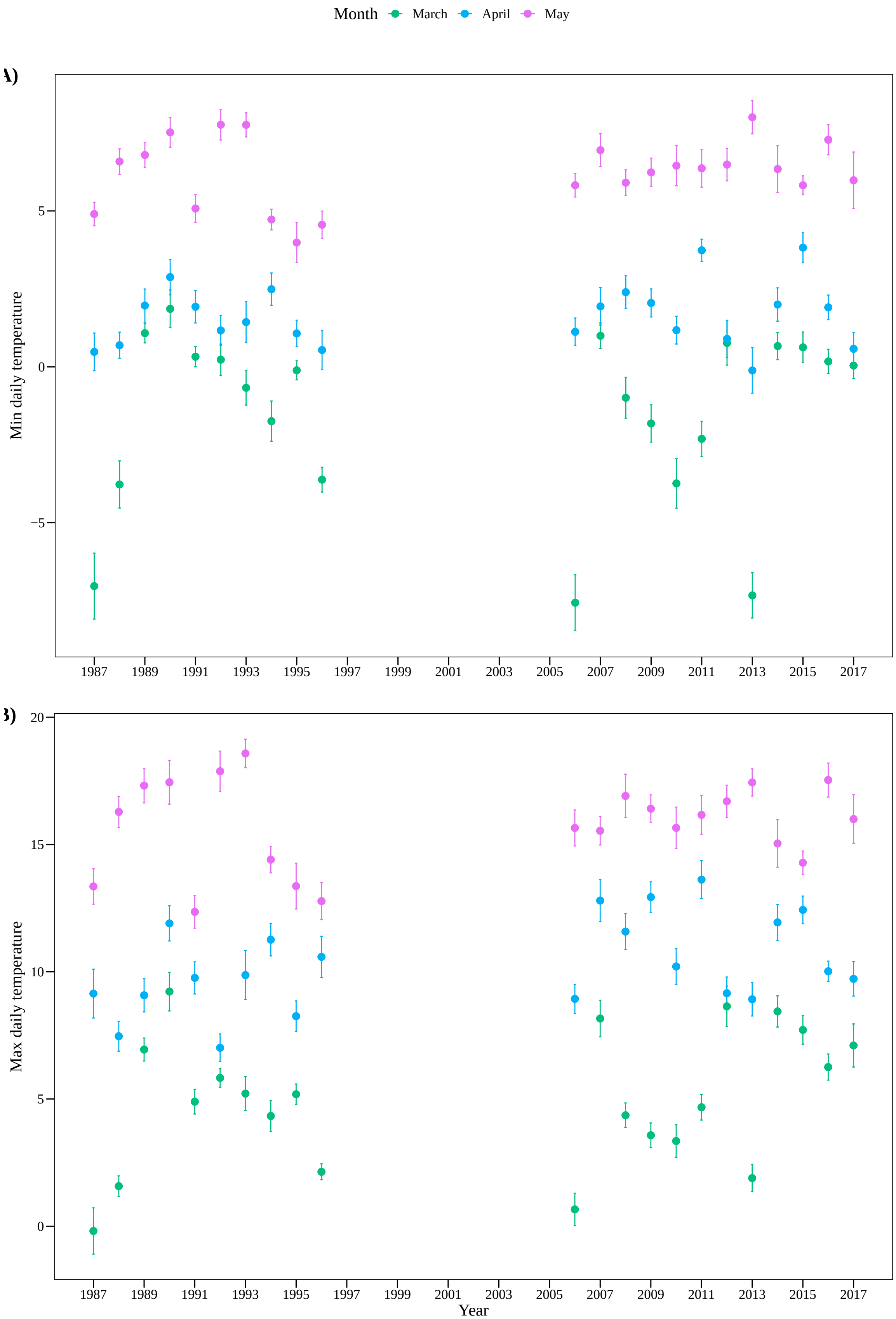


Fig. S1 - REDO WITH ALL DATA



Month March April May
A)
Min daily temperature
B)
Max daily temperature
Year

Fig. S2 - REDO WITH ALL DATA

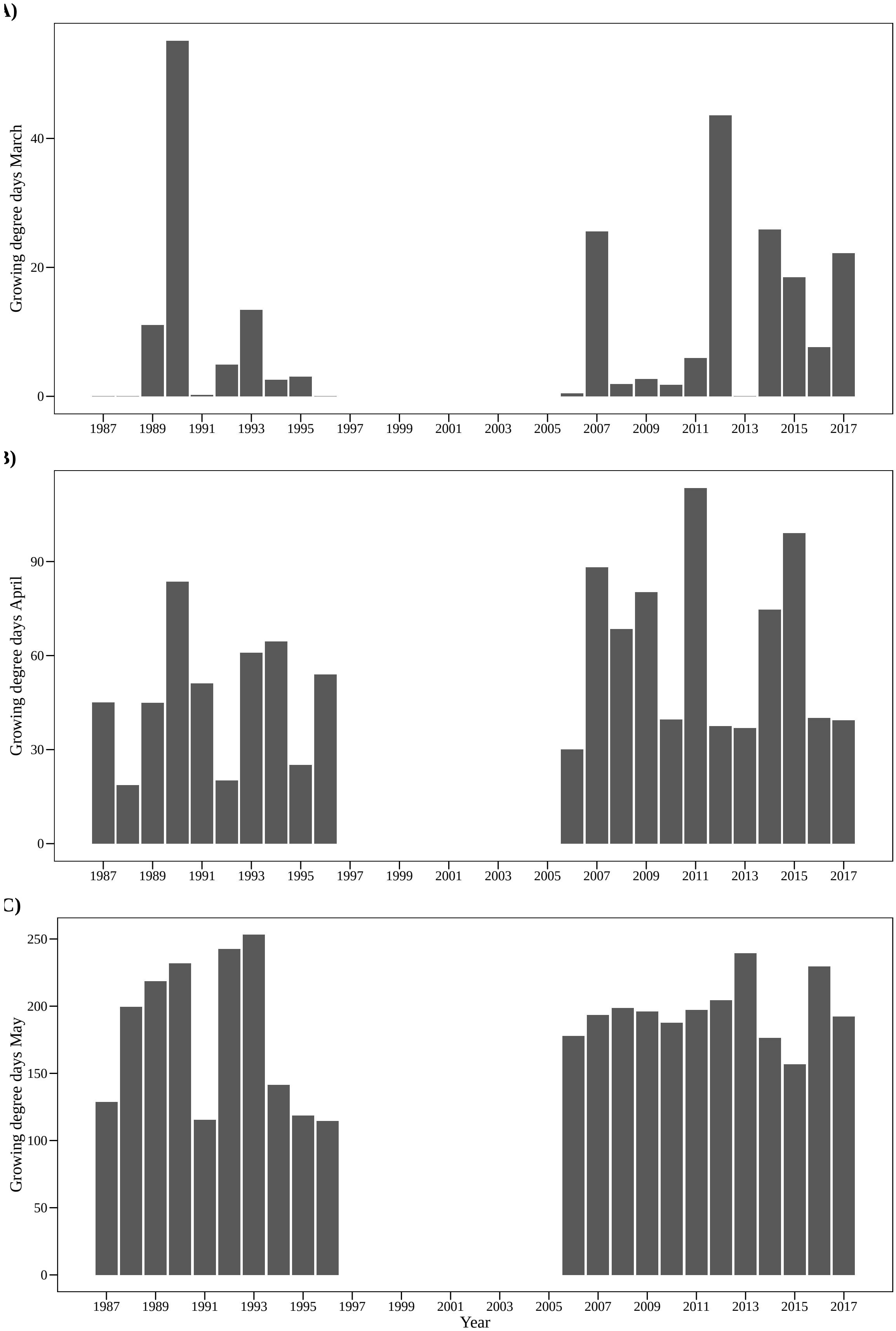
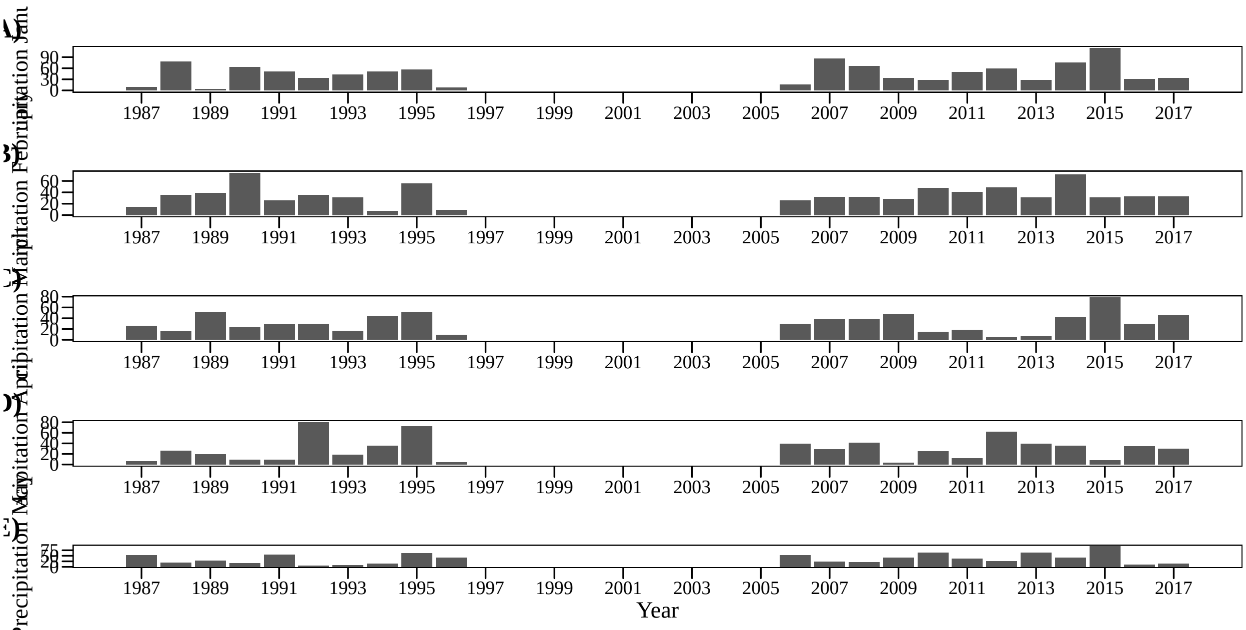


Fig. S3 - REDO WITH ALL DATA



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

FFD for each plant (Table 1A)

```
# Variables to use
subset1<-data_sel[c(2,3,86:88,158:160,170:172,182:184,189,193:196)]
subset1[,3:19]<-scale(subset1[,3:19])
globmod_FFD<-lmer(FFD ~ GDD5_3+GDD5_4+GDD5_5+max_3+max_4+max_5+mean_3+mean_4+mean_5+
                    min_3+min_4+min_5+precipitation_1+precipitation_2+precipitation_3+
                    precipitation_4+precipitation_5+(1|id),
                  data = subset1,REML=FALSE,na.action="na.fail")

# Excluding collinear variables with r > 0.5
smat1 <- abs(cor(subset1[, -c(1,2)])) <= .5 # TRUE: cor<=0.5,FALSE: cor>0.5
smat1[!lower.tri(smat1)] <- NA

clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"
clust1 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))
clusterExport(clust1, "subset1")
clusterEvalQ(clust1, library(lme4))
```

```
## [[1]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
##
## [[2]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
```

```
##
## [[3]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
```

```r
modsel_FFD<-pdredge(globmod_FFD,subset=smat1,cluster=clust1)

summary(model.avg(modsel_FFD,subset=delta<2)) # Summary averaged model
```

```
##
## Call:
## model.avg(object = modsel_FFD, subset = delta < 2)
##
## Component model call:
## lmer(formula = FFD ~ <6 unique rhs>, data = subset1, REML = FALSE,
##      na.action = na.fail)
##
## Component models:
##       df   logLik     AICc delta weight
## 3579   7 -7361.10 14736.25  0.00   0.32
## 35679  8 -7360.90 14737.86  1.61   0.14
## 13579  8 -7360.91 14737.87  1.62   0.14
## 35789  8 -7360.94 14737.95  1.70   0.14
## 23579  8 -7361.03 14738.12  1.87   0.13
## 34579  8 -7361.08 14738.22  1.97   0.12
##
## Term codes:
##          GDD5_3           max_3           max_5          mean_3
##               1               2               3               4
##          mean_4           min_3 precipitation_1 precipitation_2
##               5               6               7               8
## precipitation_3
##               9
##
## Model-averaged coefficients:
## (full average)
##                   Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)      59.123853   0.127951    0.128016 461.848   <2e-16 ***
## max_5            -3.832210   0.113738    0.113794  33.677   <2e-16 ***
## mean_4           -1.731603   0.119593    0.119653  14.472   <2e-16 ***
## precipitation_1 -1.212070   0.116218    0.116275  10.424   <2e-16 ***
## precipitation_3 -0.928597   0.111722    0.111778   8.307   <2e-16 ***
## min_3             0.012414   0.059342    0.059364   0.209    0.834
## GDD5_3            0.011109   0.053938    0.053959   0.206    0.837
## precipitation_2 -0.010125   0.054451    0.054472   0.186    0.853
## max_3            -0.006604   0.052554    0.052578   0.126    0.900
## mean_3            0.003576   0.049034    0.049058   0.073    0.942
##
## (conditional average)
##                  Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)      59.12385    0.12795     0.12802 461.848   <2e-16 ***
## max_5            -3.83221    0.11374     0.11379  33.677   <2e-16 ***
## mean_4           -1.73160    0.11959     0.11965  14.472   <2e-16 ***
## precipitation_1 -1.21207    0.11622     0.11628  10.424   <2e-16 ***
## precipitation_3 -0.92860    0.11172     0.11178   8.307   <2e-16 ***
```

```
## min_3            0.08582    0.13433     0.13440  0.639    0.523
## GDD5_3           0.07704    0.12287     0.12293  0.627    0.531
## precipitation_2 -0.07296    0.12954     0.12961  0.563    0.573
## max_3           -0.05200    0.13923     0.13930  0.373    0.709
## mean_3           0.02951    0.13812     0.13819  0.214    0.831
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      max_5 mean_4 precipitation_1 precipitation_3 min_3
## Importance:          1.00  1.00   1.00            1.00            0.14
## N containing models:    6     6      6               6               1
##                      GDD5_3 precipitation_2 max_3 mean_3
## Importance:          0.14   0.14            0.13  0.12
## N containing models:    1      1               1     1
```

```r
importance(modsel_FFD) # Variable importance
```

```
##                      precipitation_1 precipitation_3 mean_4 max_5
## Importance:              1               1               1   0.99
## N containing models:   676             676             304    216
##                      precipitation_4 min_3 GDD5_3 precipitation_2 max_3
## Importance:           0.27            0.15  0.14   0.14            0.13
## N containing models:   676             224   280    120             224
##                      mean_3 mean_5 min_4 max_4 GDD5_5 GDD5_4 min_5
## Importance:           0.12   0.01  <0.01 <0.01 <0.01  <0.01  <0.01
## N containing models:   224    176    136   304   176    304    352
##                      precipitation_5
## Importance:          <0.01
## N containing models:   392
```

```r
r.squaredGLMM(get.models(modsel_FFD,subset=1)$"20640") #R square of best model
```

```
##            R2m       R2c
## [1,] 0.4713056 0.5481503
```

FFD for each plant with year (Table S3)

```r
summary(lmer(FFD ~ scale(max_5)+scale(mean_4)+scale(precipitation_1)+scale(precipitation_3)+
               as.integer(as.character(year))+(1|id),
             data = data_sel[c(1:33,86:88,158:160,170:172,182:184,189,193:196)],
             REML=FALSE,na.action="na.fail"))
```

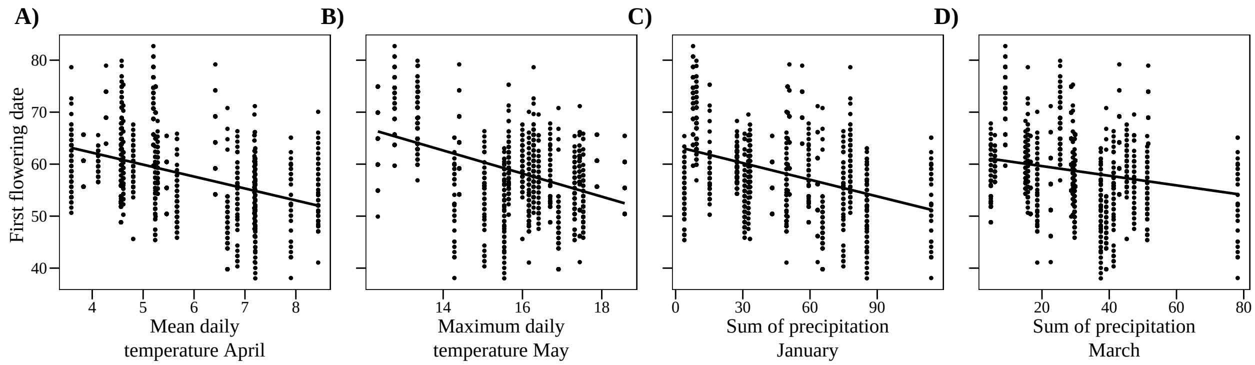
```
## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula: FFD ~ scale(max_5) + scale(mean_4) + scale(precipitation_1) +
##     scale(precipitation_3) + as.integer(as.character(year)) +
##     (1 | id)
##    Data: data_sel[c(1:33, 86:88, 158:160, 170:172, 182:184, 189, 193:196)]
##
##      AIC      BIC   logLik deviance df.resid
##  14704.5  14750.8  -7344.3  14688.5     2403
##
## Scaled residuals:
```

```
##     Min      1Q  Median      3Q     Max 
## -2.9901 -0.6856 -0.0490  0.6153  3.8528 
## 
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  2.681   1.637   
##  Residual             23.630   4.861   
## Number of obs: 2411, groups:  id, 834
## 
## Fixed effects:
##                                Estimate Std. Error         df t value
## (Intercept)                   209.23418   23.93841  811.76728   8.741
## scale(max_5)                   -3.70750    0.10754 2312.65132 -34.475
## scale(mean_4)                  -1.63106    0.11828 2213.39344 -13.790
## scale(precipitation_1)         -1.20454    0.10992 2253.91824 -10.958
## scale(precipitation_3)         -0.86563    0.10997 2271.63874  -7.871
## as.integer(as.character(year))  -0.07513    0.01198  808.91710  -6.273
##                                Pr(>|t|)    
## (Intercept)                     < 2e-16 ***
## scale(max_5)                    < 2e-16 ***
## scale(mean_4)                   < 2e-16 ***
## scale(precipitation_1)          < 2e-16 ***
## scale(precipitation_3)         5.39e-15 ***
## as.integer(as.character(year)) 5.77e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Correlation of Fixed Effects:
##             (Intr) sc(_5) sc(_4) sc(_1) sc(_3)
## scale(mx_5)  0.223                            
## scale(mn_4)  0.189  0.031                     
## scl(prcp_1)  0.009 -0.141 -0.298              
## scl(prcp_3)  0.088  0.158 -0.306 -0.036       
## as.ntg(.()) -1.000 -0.223 -0.189 -0.009 -0.088
```

```r
r.squaredGLMM(lmer(FFD ~ scale(max_5)+scale(mean_4)+scale(precipitation_1)+scale(precipitation_3)+
               as.integer(as.character(year))+(1|id),
             data = data_sel[c(1:3,86:88,158:160,170:172,182:184,189,193:196)],
             REML=FALSE,na.action="na.fail"))
```

```
##            R2m       R2c
## [1,] 0.4958144 0.5471919
```

Fig. 2: Response of FFD for each plant to climate



Position (Table 1B)

Use the same variables as in model selection for FFD for each plant

```
globmod_FFD_mean<-lm(FFD_mean~scale(mean_4)+scale(max_5)+
                       scale(precipitation_1)+scale(precipitation_3),
                     data = mean_weather4,na.action="na.fail")
modsel_FFD_mean<-dredge(globmod_FFD_mean)
```

```
## Fixed term is "(Intercept)"
```

```
summary(model.avg(modsel_FFD_mean,subset=delta<2)) # Summary averaged model
```

```
##
## Call:
## model.avg(object = modsel_FFD_mean, subset = delta < 2)
##
## Component model call:
## lm(formula = FFD_mean ~ <2 unique rhs>, data = mean_weather4,
##      na.action = na.fail)
##
## Component models:
##     df  logLik   AICc delta weight
## 123  5 -51.58 116.92  0.00   0.64
## 12   4 -53.88 118.11  1.19   0.36
##
## Term codes:
##             scale(max_5)           scale(mean_4) scale(precipitation_1)
##                        1                       2                      3
##
## Model-averaged coefficients:
## (full average)
##                        Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)             58.0087     0.6123      0.6554  88.511  < 2e-16
## scale(max_5)            -3.9558     0.6282      0.6723   5.884  < 2e-16
## scale(mean_4)           -2.9927     0.7438      0.7874   3.801 0.000144
## scale(precipitation_1)  -0.9056     0.8696      0.8953   1.011 0.311791
##
## (Intercept)            ***
## scale(max_5)           ***
```

```
## scale(mean_4)          ***
## scale(precipitation_1)
##
## (conditional average)
##                        Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)             58.0087     0.6123      0.6554  88.511  < 2e-16
## scale(max_5)            -3.9558     0.6282      0.6723   5.884  < 2e-16
## scale(mean_4)           -2.9927     0.7438      0.7874   3.801 0.000144
## scale(precipitation_1)  -1.4044     0.6872      0.7367   1.906 0.056598
##
## (Intercept)            ***
## scale(max_5)           ***
## scale(mean_4)          ***
## scale(precipitation_1) .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      scale(max_5) scale(mean_4) scale(precipitation_1)
## Importance:          1.00         1.00          0.64
## N containing models:    2            2             1
```

```
importance(modsel_FFD_mean) # Variable importance
```

```
##                      scale(max_5) scale(mean_4) scale(precipitation_1)
## Importance:          1.00         1.00          0.60
## N containing models:    8            8             8
##                      scale(precipitation_3)
## Importance:          0.29
## N containing models:    8
```

```
summary(get.models(modsel_FFD_mean,subset=1)$"8")$adj.r.squared #R square of best model
```

```
## [1] 0.7757409
```

```
## FFD_mean also related to temp when including year  (Table S4)
tidy(lm(FFD_mean~scale(mean_4)+scale(max_5)+year,data=mean_weather4))
```

```
## # A tibble: 4 x 5
##   term          estimate std.error statistic   p.value
##   <chr>            <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    268.     128.          2.09 0.0510
## 2 scale(mean_4)   -3.01     0.675      -4.46 0.000303
## 3 scale(max_5)    -3.72     0.642      -5.79 0.0000173
## 4 year            -0.105    0.0640     -1.64 0.119
```

```
glance(lm(FFD_mean~scale(mean_4)+scale(max_5)+year,data=mean_weather4))$adj.r.squared # Rsquare
```

```
## [1] 0.7595706
```

```
globmod_date_10<-lm(date_10~scale(mean_4)+scale(max_5)+
                      scale(precipitation_1)+scale(precipitation_3),
                     data = mean_weather4,na.action="na.fail")
modsel_date_10<-dredge(globmod_date_10)
```

```
## Fixed term is "(Intercept)"
```

```r
#Only one model with delta<2
summary(get.models(modsel_date_10,subset=1)$"8")
```

```
##
## Call:
## lm(formula = date_10 ~ scale(max_5) + scale(mean_4) + scale(precipitation_1) +
##     1, data = mean_weather4, na.action = "na.fail")
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1776 -2.3761  0.3257  2.6468  5.0135
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             51.3422     0.6826  75.214  < 2e-16 ***
## scale(max_5)            -3.3712     0.6998  -4.817 0.000138 ***
## scale(mean_4)           -3.6925     0.7874  -4.689 0.000183 ***
## scale(precipitation_1)  -2.0660     0.7886  -2.620 0.017355 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.202 on 18 degrees of freedom
## Multiple R-squared:  0.7999, Adjusted R-squared:  0.7665
## F-statistic: 23.98 on 3 and 18 DF,  p-value: 1.641e-06
```

```r
importance(modsel_date_10) # Variable importance
```

```
##                      scale(mean_4) scale(max_5) scale(precipitation_1)
## Importance:          1.00          1.00         0.84
## N containing models:    8             8            8
##                      scale(precipitation_3)
## Importance:          0.22
## N containing models:    8
```

```r
## date_10 also related to temp when including year  (Table S4)
tidy(lm(date_10~scale(mean_4)+scale(max_5)+scale(precipitation_1)+year,data=mean_weather4))
```

```
## # A tibble: 5 x 5
##   term                   estimate std.error statistic  p.value
##   <chr>                     <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)            156.      144.          1.08  0.295
## 2 scale(mean_4)           -3.52      0.833     -4.22  0.000574
## 3 scale(max_5)            -3.27      0.722     -4.53  0.000298
## 4 scale(precipitation_1)  -2.01      0.802     -2.51  0.0225
## 5 year                    -0.0524    0.0722    -0.726 0.478
```

```r
glance(lm(date_10~scale(mean_4)+scale(max_5)+scale(precipitation_1)+year,
          data=mean_weather4))$adj.r.squared # Rsquare
```

```
## [1] 0.7602507
```

```r
globmod_date_90<-lm(date_90~scale(mean_4)+scale(max_5)+
                      scale(precipitation_1)+scale(precipitation_3),
                     data = mean_weather4,na.action="na.fail")
modsel_date_90<-dredge(globmod_date_90)
```

```
## Fixed term is "(Intercept)"
```

```r
summary(model.avg(modsel_date_90,subset=delta<2)) # Summary averaged model
```

```
##
## Call:
## model.avg(object = modsel_date_90, subset = delta < 2)
##
## Component model call:
## lm(formula = date_90 ~ <3 unique rhs>, data = mean_weather4,
##      na.action = na.fail)
##
## Component models:
##     df logLik   AICc delta weight
## 12   4 -47.40 105.15  0.00   0.43
## 123  5 -45.95 105.66  0.51   0.33
## 124  5 -46.28 106.32  1.17   0.24
##
## Term codes:
##           scale(max_5)          scale(mean_4) scale(precipitation_1)
##                      1                      2                      3
## scale(precipitation_3)
##                      4
##
## Model-averaged coefficients:
## (full average)
##                        Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)             62.8290     0.4701      0.5030 124.900  < 2e-16
## scale(max_5)            -4.6866     0.4883      0.5221   8.977  < 2e-16
## scale(mean_4)           -1.8985     0.5411      0.5753   3.300 0.000966
## scale(precipitation_1)  -0.2807     0.5025      0.5162   0.544 0.586584
## scale(precipitation_3)  -0.1768     0.4097      0.4220   0.419 0.675187
##
## (Intercept)            ***
## scale(max_5)           ***
## scale(mean_4)          ***
## scale(precipitation_1)
## scale(precipitation_3)
##
## (conditional average)
##                        Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)             62.8290     0.4701      0.5030 124.900  < 2e-16
## scale(max_5)            -4.6866     0.4883      0.5221   8.977  < 2e-16
## scale(mean_4)           -1.8985     0.5411      0.5753   3.300 0.000966
## scale(precipitation_1)  -0.8451     0.5321      0.5703   1.482 0.138399
## scale(precipitation_3)  -0.7402     0.5346      0.5730   1.292 0.196473
##
## (Intercept)            ***
## scale(max_5)           ***
## scale(mean_4)          ***
## scale(precipitation_1)
## scale(precipitation_3)
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
```

```
##                         scale(max_5) scale(mean_4) scale(precipitation_1)
## Importance:             1.00         1.00          0.33
## N containing models:       3            3             1
##                         scale(precipitation_3)
## Importance:             0.24
## N containing models:       1
```

```
importance(modsel_date_90) # Variable importance
```

```
##                         scale(max_5) scale(mean_4) scale(precipitation_1)
## Importance:             1.00         0.97          0.40
## N containing models:       8            8             8
##                         scale(precipitation_3)
## Importance:             0.31
## N containing models:       8
```

```
summary(get.models(modsel_date_90,subset=1)$"4")$adj.r.squared #R square of best model
```

```
## [1] 0.8327233
```

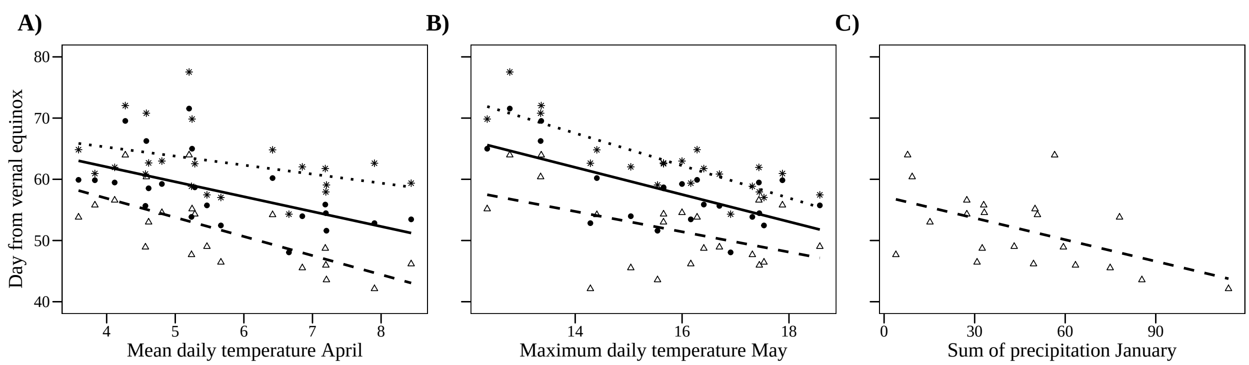
```
## date_90 also related to temp when including year  (Table S4)
tidy(lm(date_90~scale(mean_4)+scale(max_5)+year,data=mean_weather4))
```

```
## # A tibble: 4 x 5
##   term            estimate std.error statistic      p.value
##   <chr>              <dbl>     <dbl>     <dbl>        <dbl>
## 1 (Intercept)     168.        99.2        1.69 0.107
## 2 scale(mean_4)    -1.90       0.523     -3.63 0.00193
## 3 scale(max_5)     -4.54       0.497     -9.13 0.0000000355
## 4 year             -0.0526     0.0496    -1.06 0.302
```

```
glance(lm(date_90~scale(mean_4)+scale(max_5)+year,data=mean_weather4))$adj.r.squared # Rsquare
```

```
## [1] 0.8338382
```

Fig. 3: Response of position to climate



Duration (Table 1C)

```
globmod_days_90_10<-lm(days_90_10~scale(mean_4)+scale(max_5)+
                        scale(precipitation_1)+scale(precipitation_3),
```

```r
                     data = mean_weather4,na.action="na.fail")
modsel_days_90_10<-dredge(globmod_days_90_10)
```

```
## Fixed term is "(Intercept)"
```

```r
#Only one model with delta<2
summary(get.models(modsel_days_90_10,subset=1)$"8")
```

```
##
## Call:
## lm(formula = days_90_10 ~ scale(max_5) + scale(mean_4) + scale(precipitation_1) +
##     1, data = mean_weather4, na.action = "na.fail")
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -3.681 -1.467  0.338  1.486  3.313
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              11.4868     0.4336  26.494 7.16e-16 ***
## scale(max_5)             -1.3057     0.4445  -2.937 0.008803 **
## scale(mean_4)             1.9848     0.5002   3.968 0.000901 ***
## scale(precipitation_1)   1.2209     0.5009   2.438 0.025387 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.034 on 18 degrees of freedom
## Multiple R-squared:  0.731,  Adjusted R-squared:  0.6861
## F-statistic:  16.3 on 3 and 18 DF,  p-value: 2.264e-05
```

```r
importance(modsel_days_90_10) # Variable importance
```

```
##                        scale(mean_4) scale(max_5) scale(precipitation_1)
## Importance:            0.99          0.91         0.79
## N containing models:      8             8            8
##                        scale(precipitation_3)
## Importance:            0.16
## N containing models:      8
```

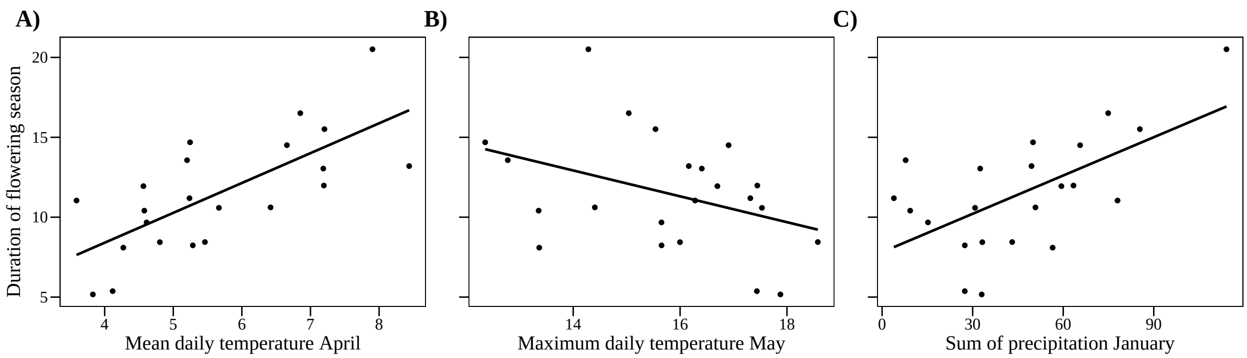
```r
## days_90_10 also related to temp when including year  (Table S4)
tidy(lm(days_90_10~scale(mean_4)+scale(max_5)+scale(precipitation_1)+year,data=mean_weather4))
```

```
## # A tibble: 5 x 5
##   term                   estimate std.error statistic p.value
##   <chr>                     <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)            -0.940     93.1      -0.0101 0.992
## 2 scale(mean_4)           1.96       0.537     3.66   0.00195
## 3 scale(max_5)           -1.32       0.466    -2.83   0.0116
## 4 scale(precipitation_1)  1.21       0.517     2.35   0.0312
## 5 year                    0.00621    0.0465    0.133  0.895
```

```r
glance(lm(days_90_10~scale(mean_4)+scale(max_5)+scale(precipitation_1)+year,
          data=mean_weather4))$adj.r.squared # Rsquare
```

```
## [1] 0.668018
```

Fig. 4: Response of duration of the flowering season to climate



Results 3: Response of fitness to climate, mean position and duration of flowering

Climate (Table 2A)

```
# Variables to use
subset2<-data_sel[c(3,20,42,86:88,158:160,170:172,182:184,189,193:196)]

subset2[,c(3:20)]<-scale(subset2[,c(3:20)])
globmod_fitness<-lmer(n_intact_seeds ~ GDD5_3+GDD5_4+GDD5_5+max_3+max_4+max_5+
                         mean_3+mean_4+mean_5+min_3+min_4+min_5+precipitation_1+
                         precipitation_2+precipitation_3+precipitation_4+precipitation_5+
                         n_fl+(1|id),data = subset2,REML=FALSE,na.action="na.fail")

# Excluding collinear variables with r > 0.5
smat2 <- abs(cor(subset2[, -c(1:3)])) <= .5 # TRUE: cor<=0.5,FALSE: cor>0.5
smat2[!lower.tri(smat2)] <- NA

clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"
clust1 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))
clusterExport(clust1, "subset2")
clusterEvalQ(clust1, library(lme4))
```

```
## [[1]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
##
## [[2]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
##
## [[3]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
```

```
modsel_fitness<-pdredge(globmod_fitness,subset=smat2,fixed="n_fl",cluster=clust1)
```

```
## Fixed terms are "n_fl" and "(Intercept)"
```

```r
summary(model.avg(modsel_fitness,subset=delta<2)) # Summary averaged model
```

```
##
## Call:
## model.avg(object = modsel_fitness, subset = delta < 2)
##
## Component model call:
## lmer(formula = n_intact_seeds ~ <8 unique rhs>, data = subset2,
##      REML = FALSE, na.action = na.fail)
##
## Component models:
##                    df   logLik     AICc delta weight
## 1/4/6/7/9/10        9 -8518.83 17055.74  0.00   0.23
## 1/4/6/7/9/10/11    10 -8518.39 17056.87  1.13   0.13
## 1/2/6/7/9/10        9 -8519.44 17056.96  1.22   0.13
## 1/2/7/9/10          8 -8520.59 17057.24  1.50   0.11
## 1/3/4/7/9/10        9 -8519.61 17057.29  1.55   0.11
## 1/4/7/9/10          8 -8520.62 17057.31  1.57   0.11
## 1/5/6/7/8/10        9 -8519.68 17057.43  1.69   0.10
## 1/4/6/7/8/9/10     10 -8518.77 17057.62  1.88   0.09
##
## Term codes:
##         GDD5_3          GDD5_4          GDD5_5           max_4
##              1               2               3               4
##          min_4           min_5            n_fl precipitation_1
##              5               6               7               8
## precipitation_3 precipitation_4 precipitation_5
##              9              10              11
##
## Model-averaged coefficients:
## (full average)
##                    Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)         5.05034    0.18264     0.18273  27.638  < 2e-16 ***
## GDD5_3             -0.57632    0.21621     0.21630   2.664  0.00771 **
## max_4              -0.45262    0.36804     0.36808   1.230  0.21882
## min_5              -0.25765    0.24529     0.24534   1.050  0.29365
## precipitation_3     0.44853    0.22964     0.22971   1.953  0.05087 .
## precipitation_4    -0.77996    0.26304     0.26312   2.964  0.00303 **
## n_fl                3.70007    0.17622     0.17631  20.987  < 2e-16 ***
## precipitation_5    -0.02490    0.09712     0.09715   0.256  0.79769
## GDD5_4             -0.15435    0.29832     0.29834   0.517  0.60490
## GDD5_5             -0.03037    0.10961     0.10963   0.277  0.78175
## min_4               0.06200    0.19661     0.19662   0.315  0.75252
## precipitation_1    -0.04927    0.15507     0.15509   0.318  0.75071
##
## (conditional average)
##                    Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)          5.0503     0.1826      0.1827  27.638  < 2e-16 ***
## GDD5_3              -0.5763     0.2162      0.2163   2.664  0.00771 **
## max_4               -0.6801     0.2210      0.2211   3.076  0.00210 **
## min_5               -0.3799     0.2056      0.2057   1.847  0.06479 .
## precipitation_3      0.4980     0.1842      0.1843   2.702  0.00689 **
## precipitation_4     -0.7800     0.2630      0.2631   2.964  0.00303 **
## n_fl                 3.7001     0.1762      0.1763  20.987  < 2e-16 ***
```

```
## precipitation_5  -0.1895     0.2015      0.2016   0.940  0.34725
## GDD5_4           -0.6564     0.2212      0.2213   2.965  0.00302 **
## GDD5_5           -0.2853     0.2003      0.2004   1.424  0.15454
## min_4             0.6244     0.1953      0.1954   3.196  0.00139 **
## precipitation_1  -0.2599     0.2685      0.2686   0.968  0.33318
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      GDD5_3 n_fl precipitation_4 precipitation_3 min_5
## Importance:          1.00   1.00 1.00            0.90            0.68
## N containing models:    8      8    8               7               5
##                      max_4 GDD5_4 precipitation_1 precipitation_5 GDD5_5
## Importance:          0.67  0.24   0.19            0.13            0.11
## N containing models:    5     2      2               1               1
##                      min_4
## Importance:          0.10
## N containing models:    1
```

```r
importance(modsel_fitness) # Variable importance
```

```
##                      n_fl  precipitation_4 GDD5_3 precipitation_3 min_5
## Importance:             1   0.89            0.87   0.76            0.49
## N containing models:  1352   676             280    676             352
##                      precipitation_1 max_4 GDD5_4 min_4 precipitation_5
## Importance:           0.45            0.42  0.28   0.27  0.21
## N containing models:   676             304   304    136   392
##                      GDD5_5 mean_5 max_5 max_3 min_3 mean_3 mean_4
## Importance:           0.17   0.09   0.07  0.05  0.02  0.01   <0.01
## N containing models:   176    176    216   224   224   224    304
##                      precipitation_2
## Importance:          <0.01
## N containing models:   120
```

```r
r.squaredGLMM(get.models(modsel_fitness,subset=1)$"51217") #R square of best model
```

```
##            R2m       R2c
## [1,] 0.1782453 0.2154686
```

Position (Table 2B)

```r
summary(lmer(n_intact_seeds~FFD_mean+n_fl+(1|id),data=data_sel)) #NS
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: n_intact_seeds ~ FFD_mean + n_fl + (1 | id)
##    Data: data_sel
##
## REML criterion at convergence: 17112.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.4781 -0.4580 -0.3133  0.2552  9.6781
##
```

```
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  3.524   1.877
##  Residual             67.250   8.201
## Number of obs: 2411, groups:  id, 834
##
## Fixed effects:
##              Estimate Std. Error        df t value Pr(>|t|)
## (Intercept) 2.172e+00  1.889e+00 2.192e+03   1.150    0.250
## FFD_mean    2.163e-03  3.139e-02 2.259e+03   0.069    0.945
## n_fl        2.078e-01  1.019e-02 2.072e+03  20.400   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) FFD_mn
## FFD_mean -0.993
## n_fl     -0.218  0.152
```

```
r.squaredGLMM(lmer(n_intact_seeds~FFD_mean+n_fl+(1|id),data=data_sel)) #NS
```

```
##            R2m       R2c
## [1,] 0.1588836 0.2007685
```

Duration (Table 2C)

```
summary(lmer(n_intact_seeds~days_90_10+n_fl+(1|id),data=data_sel)) #*
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: n_intact_seeds ~ days_90_10 + n_fl + (1 | id)
##    Data: data_sel
##
## REML criterion at convergence: 17066.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.5252 -0.4728 -0.2742  0.2428  9.6293
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  3.758   1.939
##  Residual             65.762   8.109
## Number of obs: 2411, groups:  id, 834
##
## Fixed effects:
##               Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)   -1.87867    0.66059 2398.12173  -2.844  0.00449 **
## days_90_10     0.38394    0.05709 2353.77609   6.725  2.2e-11 ***
## n_fl           0.20085    0.01005 2048.78930  19.983  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
```

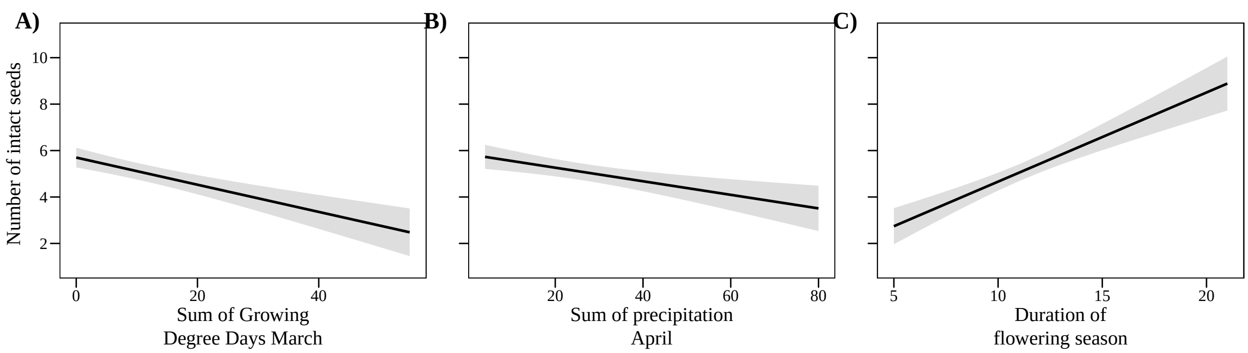
```
##             (Intr) d_90_1
## days_90_10 -0.940
## n_fl       -0.092 -0.105
```

```r
r.squaredGLMM(lmer(n_intact_seeds~days_90_10+n_fl+(1|id),data=data_sel)) #*
```

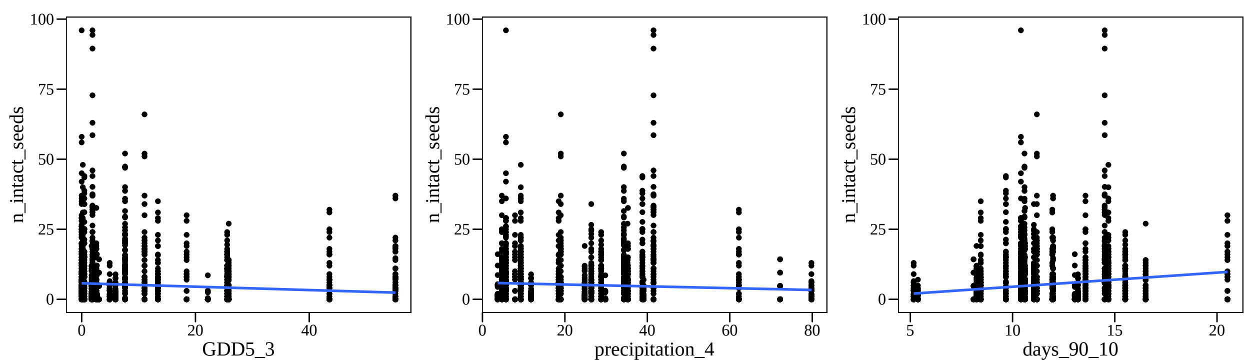
```
##            R2m       R2c
## [1,] 0.1743302 0.2189671
```

Fig. 5: Response of fitness to climate, 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



Results 4: Differences in selection among years

Indirect selection (selection differentials, Table 3A)

```r
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:year+(1|id),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      110.183  1     <2e-16 ***
## FFD_std:year  36.459 21     0.0194 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#Indirect selection for early flowering differs among years
```

Direct selection (selection gradients, Table 3B)

```
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:year+n_fl_std+(1|id),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       33.892  1  5.826e-09 ***
## n_fl_std      64.793  1  8.317e-16 ***
## FFD_std:year 37.867 21    0.01336 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#Direct selection for early flowering differs among years
```

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

Response of selection to climate, position and duration of flowering season.

```
mean_weather5<-merge(mean_weather4,subset(selgrads_FFD,term=="FFD_std")[c(1,3)])
names(mean_weather5)[156]<-"selgrad_FFD"
mean_weather5<-merge(mean_weather5,subset(seldiffs_FFD,term=="FFD_std")[c(1,3)])
names(mean_weather5)[157]<-"seldiff_FFD"
```

Analysis with selection gradients (not used)

Spring temperature

```
tidy(lm(selgrad_FFD~mean_4,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)  -0.358     0.201     -1.78   0.0901
## 2 mean_4        0.0139    0.0346     0.404  0.691
```

```
glance(lm(selgrad_FFD~mean_4,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04152097
```

Position of the flowering season

```
tidy(lm(selgrad_FFD~date_10,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.218     0.372      -0.586   0.564
## 2 date_10     -0.00118   0.00719    -0.164   0.872
```

```
glance(lm(selgrad_FFD~date_10,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04859329
```

```
tidy(lm(selgrad_FFD~FFD_mean,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term         estimate std.error statistic p.value
##   <chr>           <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.292      0.472     -0.619    0.543
## 2 FFD_mean     0.000229   0.00810    0.0283   0.978
```

```
glance(lm(selgrad_FFD~FFD_mean,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04995806
```

```
tidy(lm(selgrad_FFD~date_90,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.441     0.547      -0.806   0.430
## 2 date_90      0.00258   0.00867     0.297   0.769
```

```
glance(lm(selgrad_FFD~date_90,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04538396
```

Duration of the flowering season

```
tidy(lm(selgrad_FFD~days_90_10,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.392      0.156     -2.51   0.0206
## 2 days_90_10   0.00982    0.0130     0.758  0.457
```

```
glance(lm(selgrad_FFD~days_90_10,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.02068466
```

Analysis with selection differentials (not used)

Spring temperature

```
tidy(lm(seldiff_FFD~mean_4,data=mean_weather5))
```

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

```
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.447      0.244    -1.83    0.0819
## 2 mean_4       0.00204    0.0420    0.0486  0.962
```

```
glance(lm(seldiff_FFD~mean_4,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04987603
```

Position of the flowering season

```
tidy(lm(seldiff_FFD~date_10,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.577     0.450      -1.28    0.214
## 2 date_10      0.00275   0.00869     0.317   0.755
```

```
glance(lm(seldiff_FFD~date_10,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04475649
```

```
tidy(lm(seldiff_FFD~FFD_mean,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.597     0.570      -1.05    0.307
## 2 FFD_mean     0.00279   0.00978     0.285   0.778
```

```
glance(lm(seldiff_FFD~FFD_mean,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04573857
```

```
tidy(lm(seldiff_FFD~date_90,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.726      0.660     -1.10    0.284
## 2 date_90      0.00463    0.0105     0.442   0.663
```

```
glance(lm(seldiff_FFD~date_90,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.03984308
```

Duration of the flowering season

```
tidy(lm(seldiff_FFD~days_90_10,data=mean_weather5))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept) -0.451      0.191    -2.36    0.0285
## 2 days_90_10   0.00140    0.0159    0.0883  0.931
```

```r
glance(lm(seldiff_FFD~days_90_10,data=mean_weather5))$adj.r.squared # Rsquare
```

```
## [1] -0.04959105
```

GLMMs (Table 4)

```r
# Variables to use
subset3<-data_sel[c(3,44:46,86:88,158:160,170:172,182:184,189,193:196)]
subset3[,c(5:21)]<-scale(subset3[,c(5:21)])
globmod_selection<-lmer(n_intact_seeds_rel ~ FFD_std+n_fl_std+
                          FFD_std:GDD5_3+FFD_std:GDD5_4+FFD_std:GDD5_5+
                          FFD_std:max_3+FFD_std:max_4+FFD_std:max_5+
                          FFD_std:mean_3+FFD_std:mean_4+FFD_std:mean_5+
                          FFD_std:min_3+FFD_std:min_4+FFD_std:min_5+
                          FFD_std:precipitation_1+FFD_std:precipitation_2+
                          FFD_std:precipitation_3+FFD_std:precipitation_4+
                          FFD_std:precipitation_5+(1|id),
                        data = subset3,REML=FALSE,na.action="na.fail")

# Excluding collinear variables with r > 0.5
smat3 <- abs(cor(subset3[, -c(1:4)])) <= .5 # TRUE: cor<=0.5,FALSE: cor>0.5
smat3[!lower.tri(smat3)] <- NA
rownames(smat3)<-paste("FFD_std:", names(smat3[1,1:17]),sep="")
colnames(smat3)<-paste("FFD_std:", names(smat3[1,1:17]),sep="")

clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"
clust1 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))
clusterExport(clust1, "subset3")
clusterEvalQ(clust1, library(lme4))
```

```
## [[1]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
##
## [[2]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
##
## [[3]]
## [1] "lme4"      "Matrix"    "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
```

```r
modsel_selection<-pdredge(globmod_selection,subset=smat3,fixed=c("FFD_std","n_fl_std"),
                          cluster=clust1)
```

```
## Fixed terms are "FFD_std", "n_fl_std" and "(Intercept)"
```

```r
summary(model.avg(modsel_selection,subset=delta<2)) # Summary averaged model
```

```
##
## Call:
## model.avg(object = modsel_selection, subset = delta < 2)
##
## Component model call:
```

```
## lmer(formula = n_intact_seeds_rel ~ <11 unique rhs>, data =
##      subset3, REML = FALSE, na.action = na.fail)
##
## Component models:
##                  df   logLik     AICc delta weight
## 1/2/3/6/9/10      9 -5068.73 10155.53  0.00   0.14
## 1/2/5/6/9/10      9 -5068.79 10155.66  0.13   0.13
## 1/2/6/7/9/10      9 -5068.94 10155.96  0.43   0.11
## 1/2/4/6/9/10      9 -5069.01 10156.09  0.56   0.11
## 1/2/3/6/8/9/10   10 -5068.11 10156.32  0.79   0.09
## 1/2/5/6/8/9/10   10 -5068.23 10156.56  1.03   0.08
## 1/2/4/6/8/9/10   10 -5068.29 10156.68  1.14   0.08
## 1/2/6/9/10/11     9 -5069.47 10157.01  1.48   0.07
## 1/2/6/7/8/9/10   10 -5068.47 10157.03  1.50   0.07
## 1/2/6/9/10        8 -5070.49 10157.04  1.50   0.07
## 1/2/6/7/9/10/11  10 -5068.59 10157.27  1.74   0.06
##
## Term codes:
##                  FFD_std                n_fl_std          FFD_std:GDD5_5
##                        1                       2                       3
##            FFD_std:max_5          FFD_std:mean_5           FFD_std:min_4
##                        4                       5                       6
##            FFD_std:min_5 FFD_std:precipitation_1 FFD_std:precipitation_3
##                        7                       8                       9
## FFD_std:precipitation_4 FFD_std:precipitation_5
##                       10                      11
##
## Model-averaged coefficients:
## (full average)
##                          Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)              0.993149   0.042744    0.042765  23.223  < 2e-16
## FFD_std                 -0.265092   0.045938    0.045961   5.768  < 2e-16
## n_fl_std                 0.377250   0.046492    0.046516   8.110  < 2e-16
## FFD_std:GDD5_5           0.020089   0.042711    0.042717   0.470  0.63816
## FFD_std:min_4           -0.167390   0.051705    0.051729   3.236  0.00121
## FFD_std:precipitation_3  0.194070   0.047556    0.047579   4.079 4.53e-05
## FFD_std:precipitation_4 -0.117148   0.047292    0.047314   2.476  0.01329
## FFD_std:mean_5           0.018105   0.040847    0.040852   0.443  0.65763
## FFD_std:min_5            0.017756   0.039198    0.039205   0.453  0.65062
## FFD_std:max_5            0.014897   0.037201    0.037206   0.400  0.68887
## FFD_std:precipitation_1  0.016667   0.036281    0.036291   0.459  0.64605
## FFD_std:precipitation_5 -0.006598   0.024286    0.024291   0.272  0.78590
##
## (Intercept)             ***
## FFD_std                 ***
## n_fl_std                ***
## FFD_std:GDD5_5
## FFD_std:min_4           **
## FFD_std:precipitation_3 ***
## FFD_std:precipitation_4 *
## FFD_std:mean_5
## FFD_std:min_5
## FFD_std:max_5
## FFD_std:precipitation_1
```

```
## FFD_std:precipitation_5
##
## (conditional average)
##                          Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)               0.99315    0.04274     0.04277  23.223  < 2e-16
## FFD_std                  -0.26509    0.04594     0.04596   5.768 1.00e-08
## n_fl_std                  0.37725    0.04649     0.04652   8.110  < 2e-16
## FFD_std:GDD5_5            0.08616    0.04617     0.04619   1.865  0.06214
## FFD_std:min_4            -0.16739    0.05171     0.05173   3.236  0.00121
## FFD_std:precipitation_3  0.19407    0.04756     0.04758   4.079 4.53e-05
## FFD_std:precipitation_4 -0.11715    0.04729     0.04731   2.476  0.01329
## FFD_std:mean_5            0.08467    0.04654     0.04657   1.818  0.06903
## FFD_std:min_5             0.07502    0.04686     0.04688   1.600  0.10955
## FFD_std:max_5             0.08091    0.04664     0.04666   1.734  0.08292
## FFD_std:precipitation_1  0.05178    0.04766     0.04768   1.086  0.27746
## FFD_std:precipitation_5 -0.05285    0.04775     0.04777   1.106  0.26856
##
## (Intercept)              ***
## FFD_std                  ***
## n_fl_std                 ***
## FFD_std:GDD5_5           .
## FFD_std:min_4            **
## FFD_std:precipitation_3 ***
## FFD_std:precipitation_4 *
## FFD_std:mean_5           .
## FFD_std:min_5
## FFD_std:max_5            .
## FFD_std:precipitation_1
## FFD_std:precipitation_5
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      FFD_std n_fl_std FFD_std:min_4
## Importance:          1.00    1.00     1.00
## N containing models:   11      11       11
##                      FFD_std:precipitation_3 FFD_std:precipitation_4
## Importance:          1.00                    1.00
## N containing models:   11                      11
##                      FFD_std:precipitation_1 FFD_std:min_5 FFD_std:GDD5_5
## Importance:          0.32                    0.24          0.23
## N containing models:    4                       3             2
##                      FFD_std:mean_5 FFD_std:max_5 FFD_std:precipitation_5
## Importance:          0.21           0.18          0.12
## N containing models:    2              2             2
```

```r
importance(modsel_selection) # Variable importance
```

```
##                      FFD_std n_fl_std FFD_std:precipitation_3
## Importance:          1.00    1.00     1.00
## N containing models: 1352    1352      676
##                      FFD_std:precipitation_4 FFD_std:min_4
## Importance:          0.87                    0.74
## N containing models:  676                     136
##                      FFD_std:precipitation_1 FFD_std:GDD5_3 FFD_std:min_5
```

```
## Importance:          0.36                     0.22           0.21
## N containing models:  676                      280            352
##                      FFD_std:precipitation_5 FFD_std:GDD5_5 FFD_std:max_5
## Importance:          0.19                     0.18           0.17
## N containing models:  392                      176            216
##                      FFD_std:mean_5 FFD_std:mean_4 FFD_std:precipitation_2
## Importance:          0.16           0.10           0.09
## N containing models:  176            304            120
##                      FFD_std:GDD5_4 FFD_std:min_3 FFD_std:mean_3
## Importance:          0.09           0.04          0.04
## N containing models:  304            224           224
##                      FFD_std:max_3 FFD_std:max_4
## Importance:          0.04          0.03
## N containing models:  224           304
```

```r
r.squaredGLMM(get.models(modsel_selection,subset=1)$"50180") #R square of best model
```

```
##             R2m       R2c
## [1,] 0.07841778 0.1090378
```

```r
# Anova (Table 4A) with model including variables that were significant in the averaged model
Anova(lmer(n_intact_seeds_rel ~ FFD_std+n_fl_std+FFD_std:min_4+FFD_std:precipitation_3+FFD_std:precipita
             (1|id),data = subset3,REML=FALSE,na.action="na.fail"))
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel
##                           Chisq Df Pr(>Chisq)
## FFD_std                 33.9221  1  5.736e-09 ***
## n_fl_std                65.4987  1  5.815e-16 ***
## FFD_std:min_4            8.9389  1  0.0027917 **
## FFD_std:precipitation_3 14.4163  1  0.0001465 ***
## FFD_std:precipitation_4  3.8699  1  0.0491581 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:FFD_mean+n_fl_std+(1|id),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          33.5338  1  7.004e-09 ***
## n_fl_std         63.6116  1  1.515e-15 ***
## FFD_std:FFD_mean  0.1715  1     0.6788
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```r
Anova(lmer(n_intact_seeds_rel ~ FFD_std+FFD_std:days_90_10+n_fl_std+(1|id),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            33.5298  1  7.018e-09 ***
```

```
## n_fl_std           63.3105  1  1.766e-15 ***
## FFD_std:days_90_10  0.3042  1     0.5812
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#No influences of days_90_10 on selection on FFD
```

Fig. 6: Response of selection gradients to climate, position and duration of flowering season

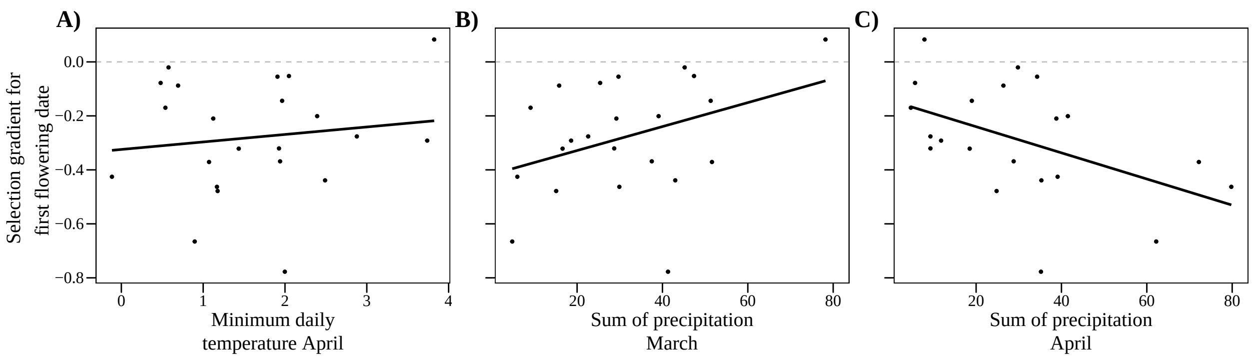


Fig. 6 alternative