

Results Lathyrus paper 1

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Temperature and precipitation data manipulation

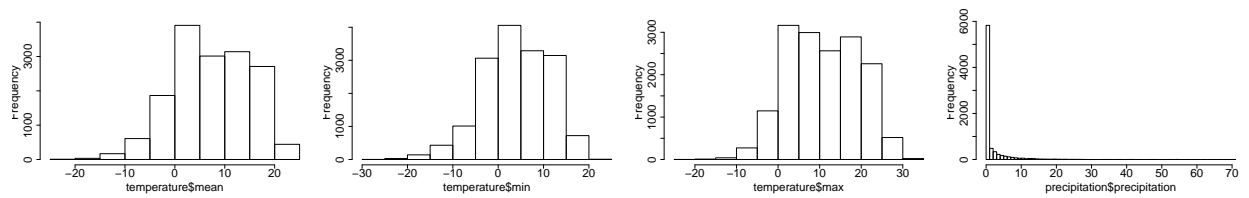
Temperature (daily mean, minimum and maximum) from two stations: Oxelösund and Södertälje
Precipitation from one station: Åda

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

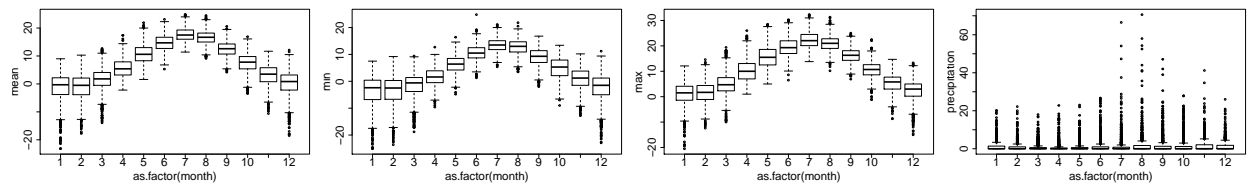
station	date	year	month	day	mean	quality_mean	min	quality_.min	max	quality_max
Oxelösund	1987-01-05	1987	1	5	-4.6	Y	-17.0	G	-1.5	G
Oxelösund	1987-01-06	1987	1	6	-10.7	Y	-14.5	G	-3.0	G

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

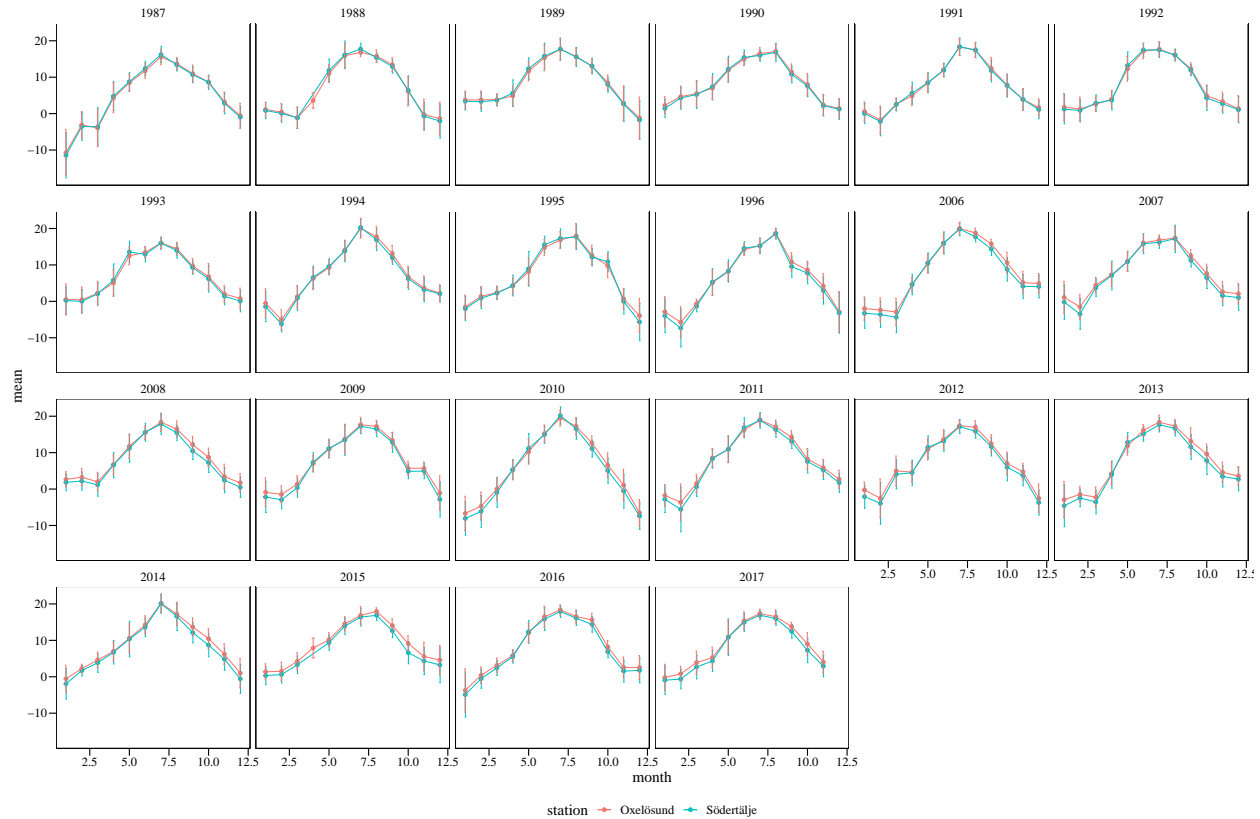
Distributions



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

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

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

```
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
```

```
#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 °C

GDD:

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

GDH:

$$\text{If } T_{\max, i} \leq 5^{\circ}\text{C} \rightarrow \text{GDH}_i = 0$$

$$\begin{aligned} \text{If } T_{\max i} > 5^{\circ}\text{C} \text{ and } T_{\min i} > 5^{\circ}\text{C} \rightarrow \\ \text{GDH}_i &= 24 \times (T_{\min i} - 5) + 12 \times (T_{\max i} - T_{\min i}) \end{aligned}$$

$$\begin{aligned} \text{If } T_{\max i} > 5^{\circ}\text{C} \text{ and } T_{\min i} \leq 5^{\circ}\text{C} \rightarrow \\ \text{GDH}_i &= 12 \times (T_{\max i} - 5)^2 / (T_{\max i} - T_{\min i}) \end{aligned}$$

```
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)))
```

```

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

```

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

```

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_subs.csv")
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

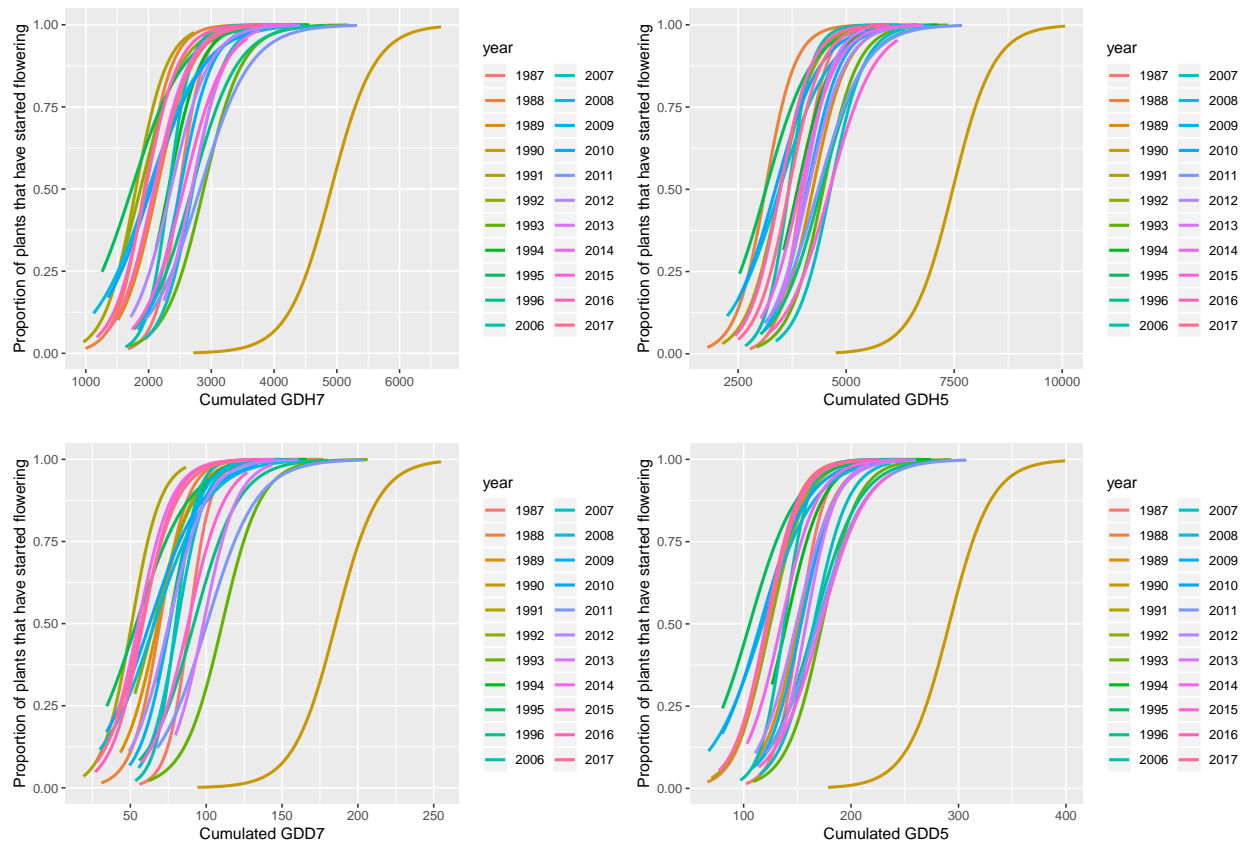
```
#Fit univariate binomial GLMs of prop_fl against each predictor
models1<-lapply(names(alldata_agg)[2:9],
  function(x) {glm(substitute(prop_fl ~ scale(i), list(i = as.name(x))),
    family=binomial, data = alldata_agg)})

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

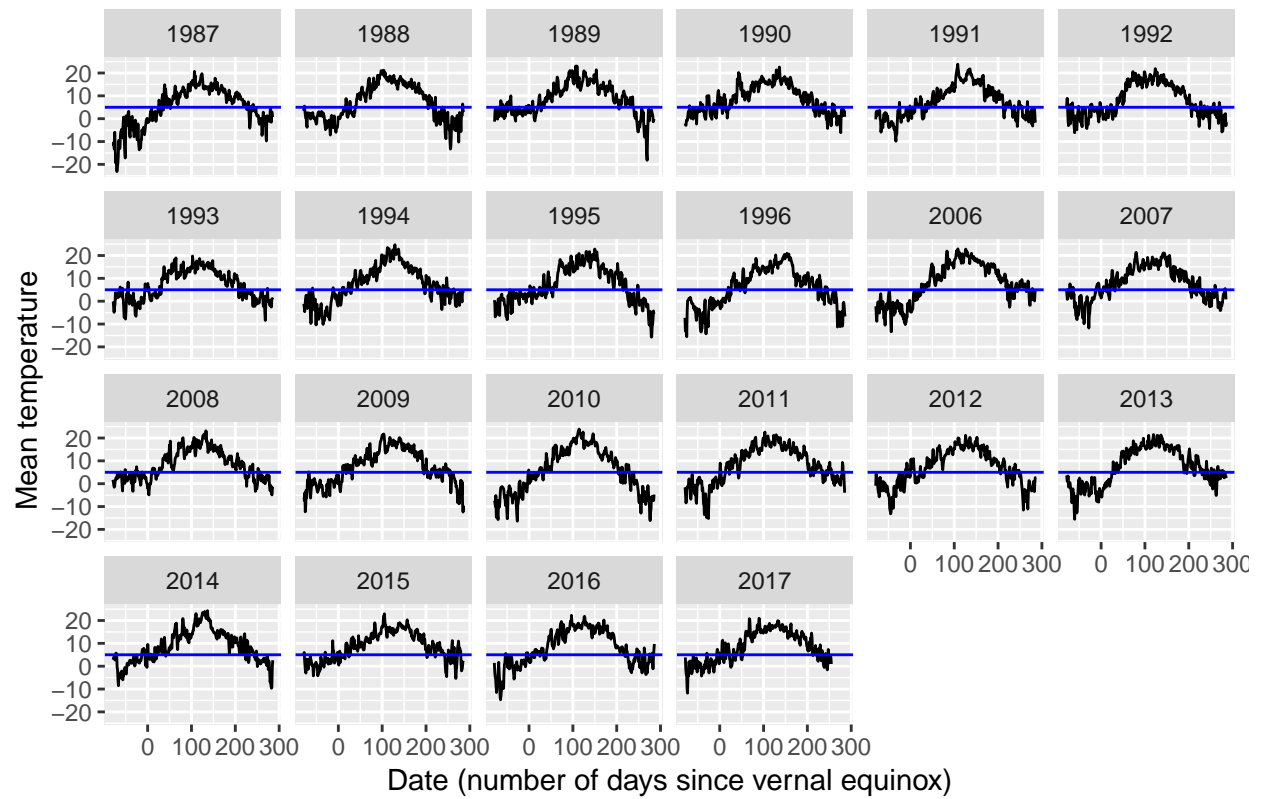
Some plots of the best models of proportion of plants that have started flowering against cumulated GDD/GDH

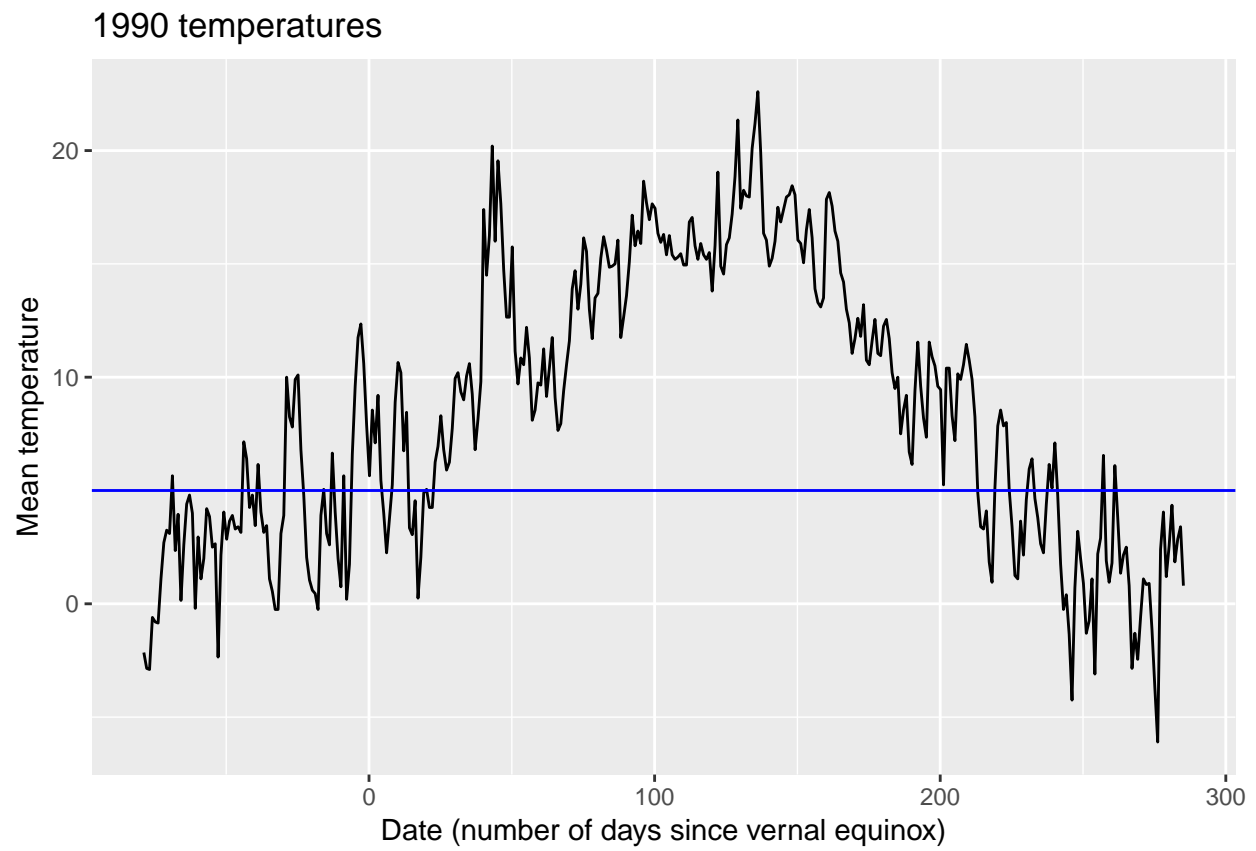


Plots for year 1990

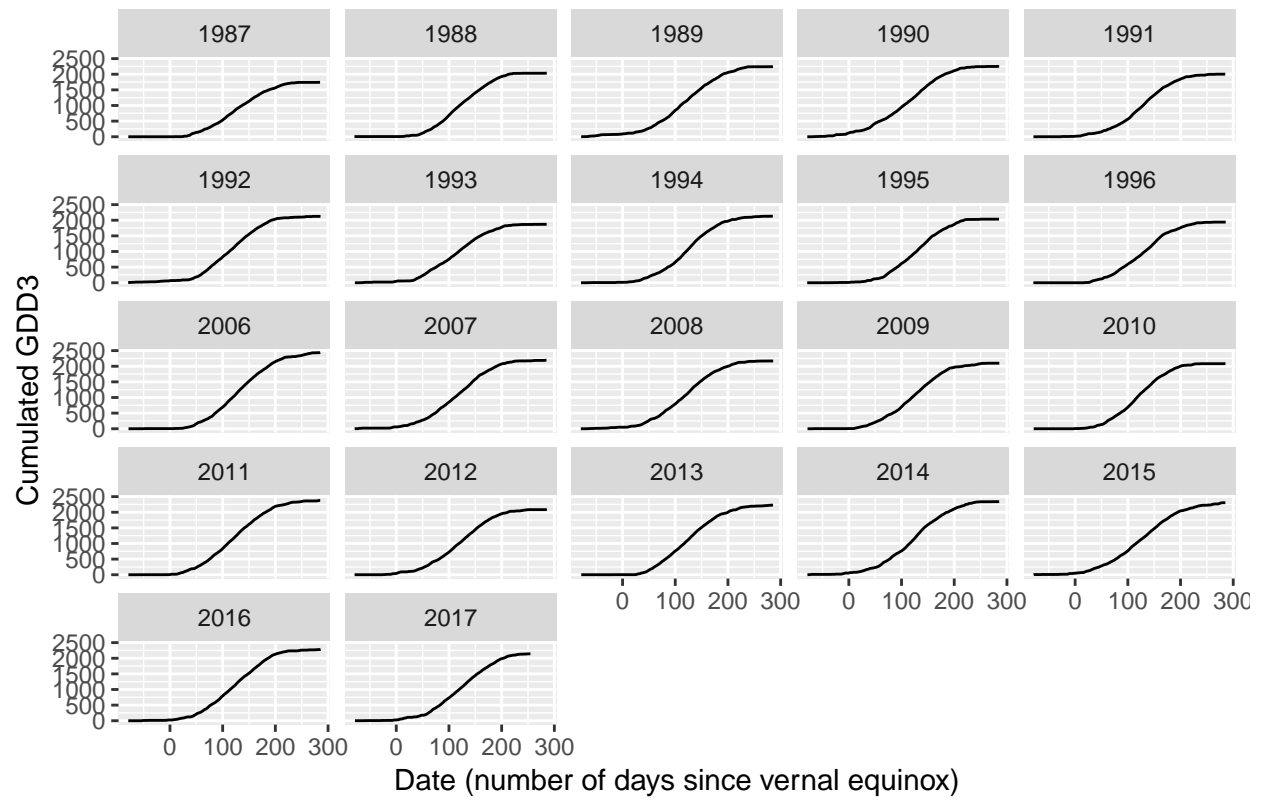
Year 1990 shows high values of GDD/GDH
Some plots to look at these high values

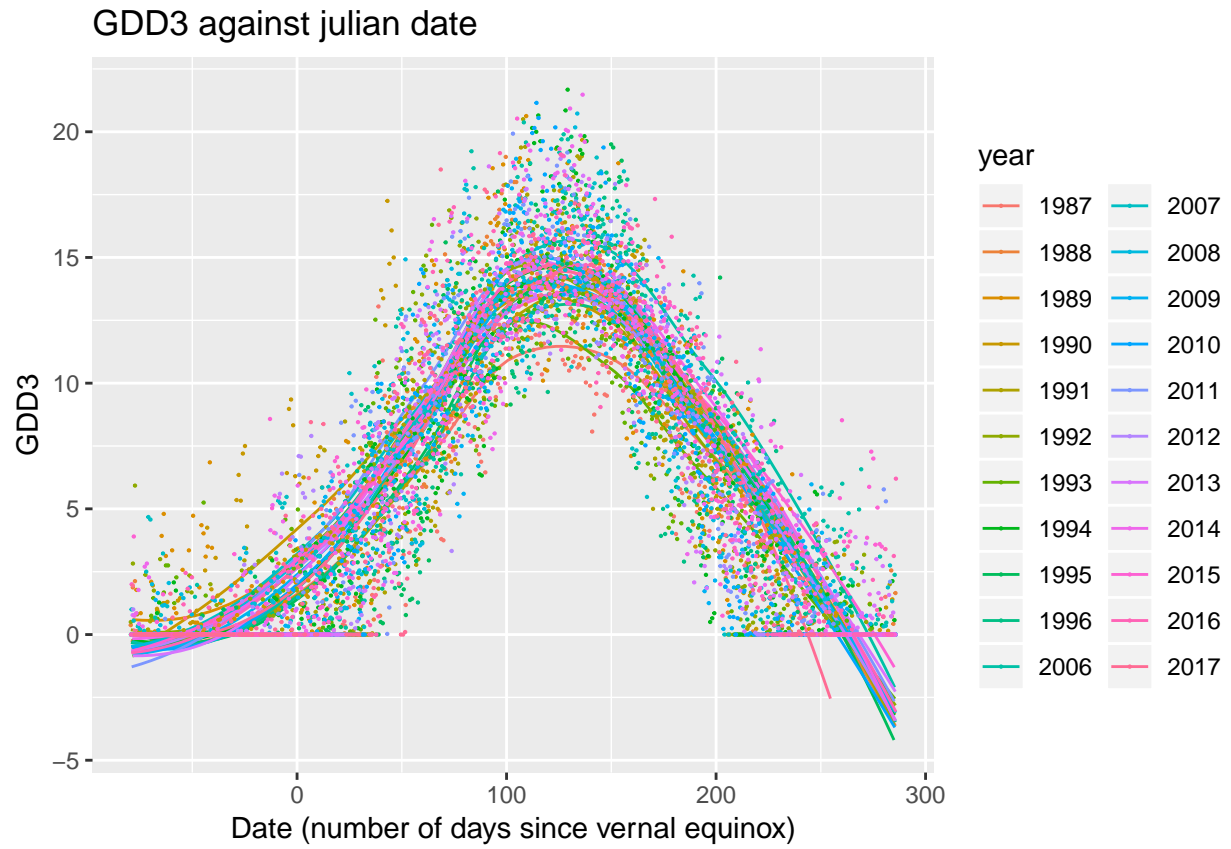
Mean temperatures for all years



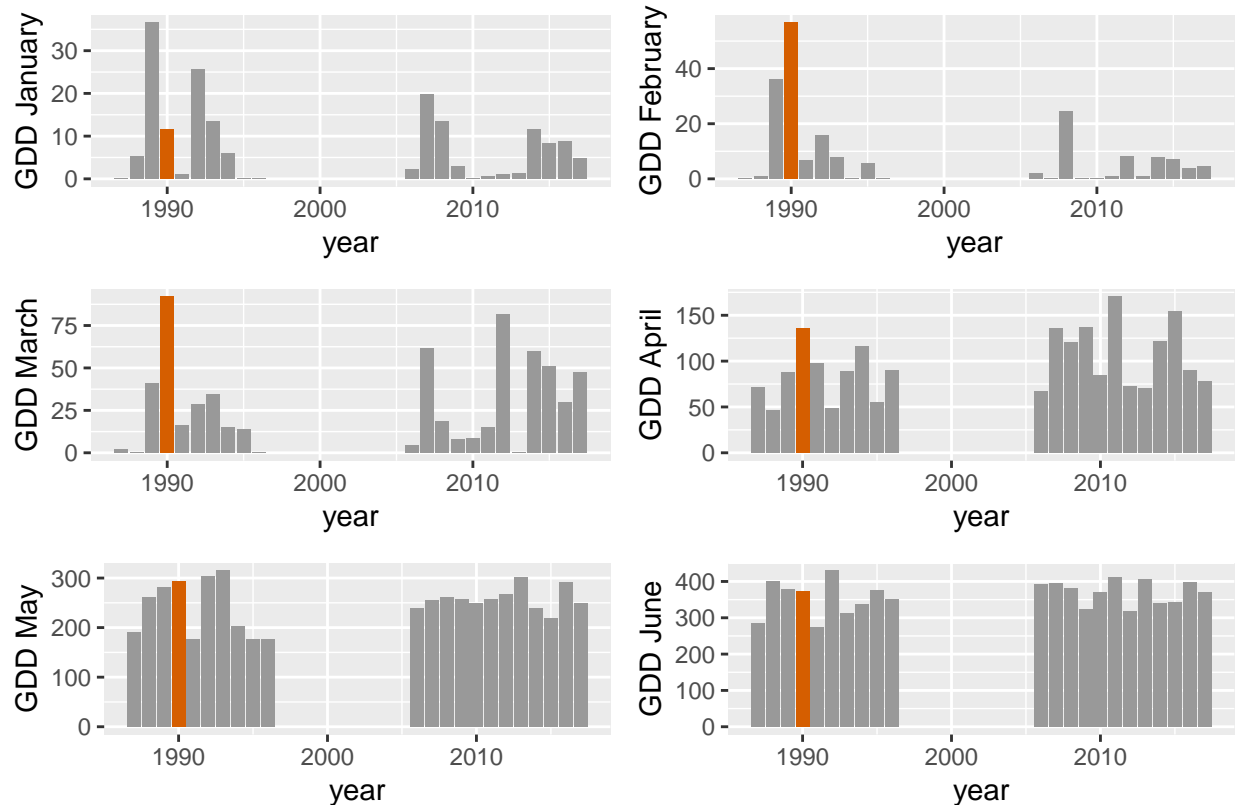


Cumulated GDD3 against julian date





GDD for different months for each year, 1990 in red



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

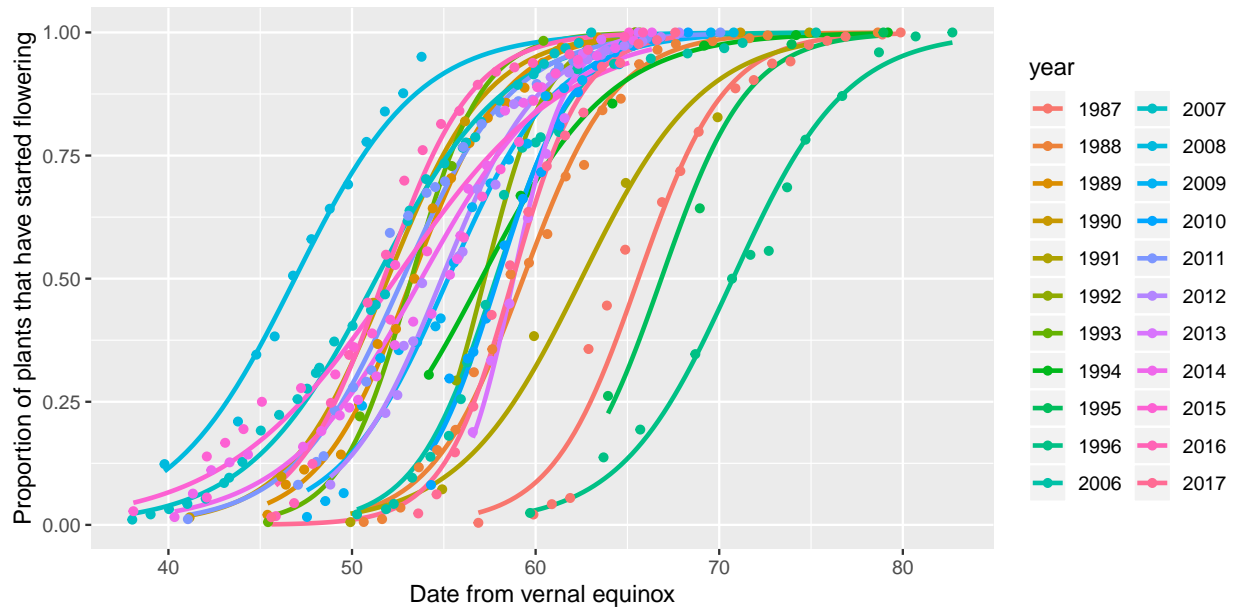
max_flowering<-aggregate(n_cum_FFD ~year, data=propfl,FUN=max)
max_flowering$max_flowering<-max_flowering$n_cum_FFD
max_flowering$n_cum_FFD<-NULL

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(nfl_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	*

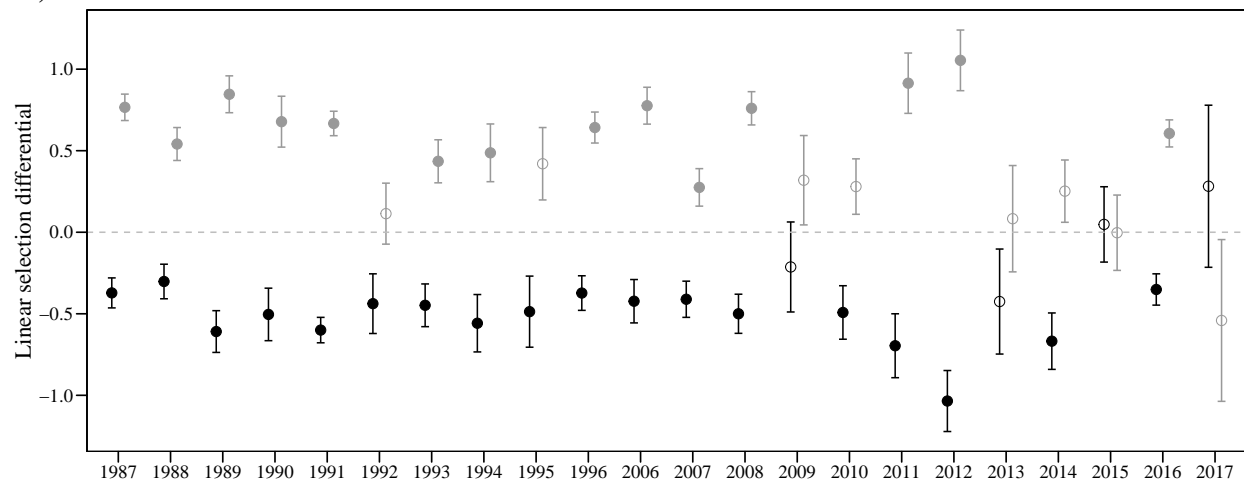
	year	term	estimate	std.error	sig
8	1990	FFD_std	-0.504	0.161	*
10	1991	FFD_std	-0.600	0.078	*
12	1992	FFD_std	-0.438	0.183	*
14	1993	FFD_std	-0.448	0.131	*
16	1994	FFD_std	-0.558	0.176	*
18	1995	FFD_std	-0.487	0.218	*
20	1996	FFD_std	-0.373	0.106	*
22	2006	FFD_std	-0.423	0.133	*
24	2007	FFD_std	-0.411	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	

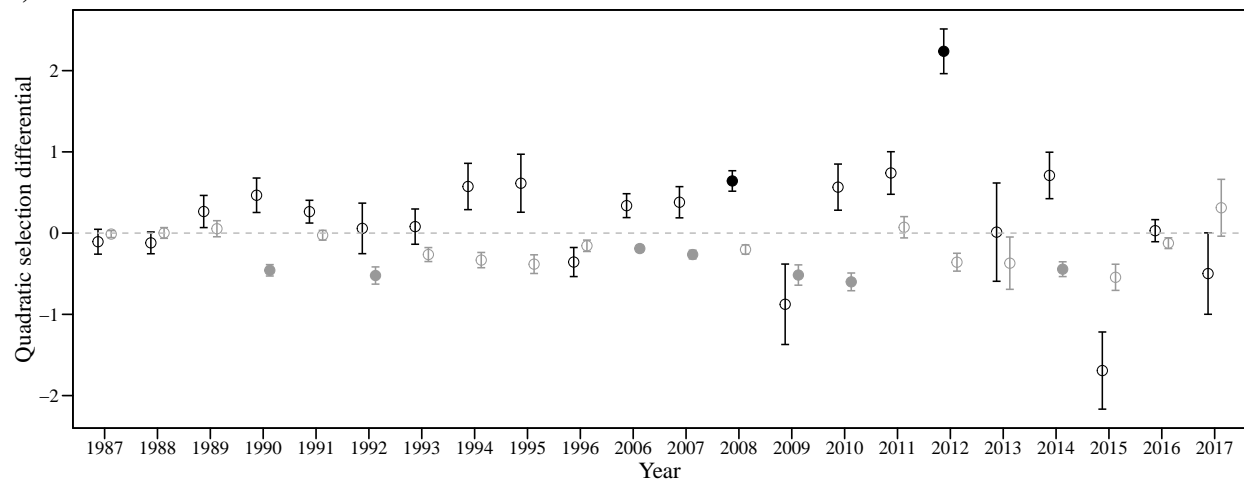
```
write.table(seldiffs,file="seldiffs.txt",sep="\t")
```

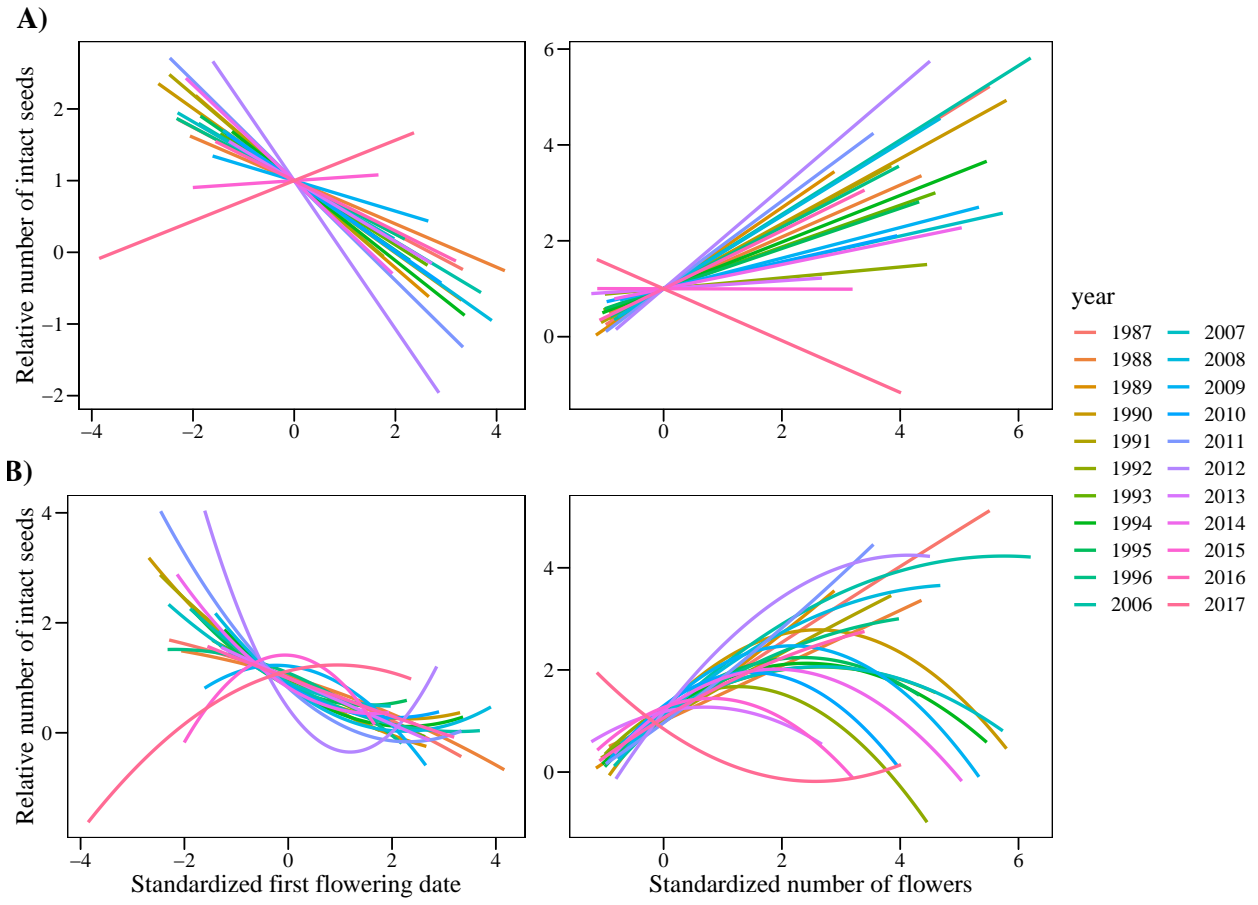
Plots

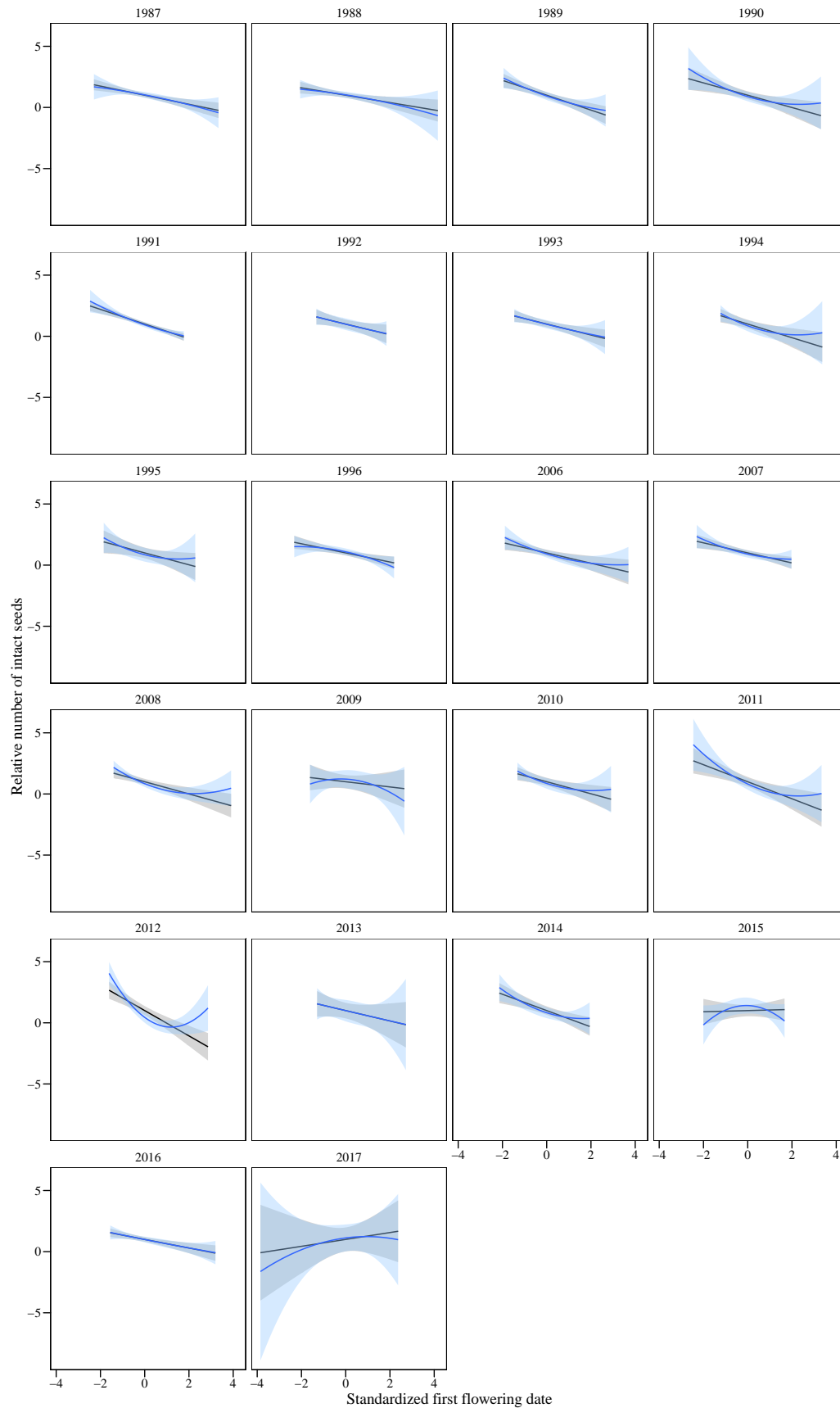
A)

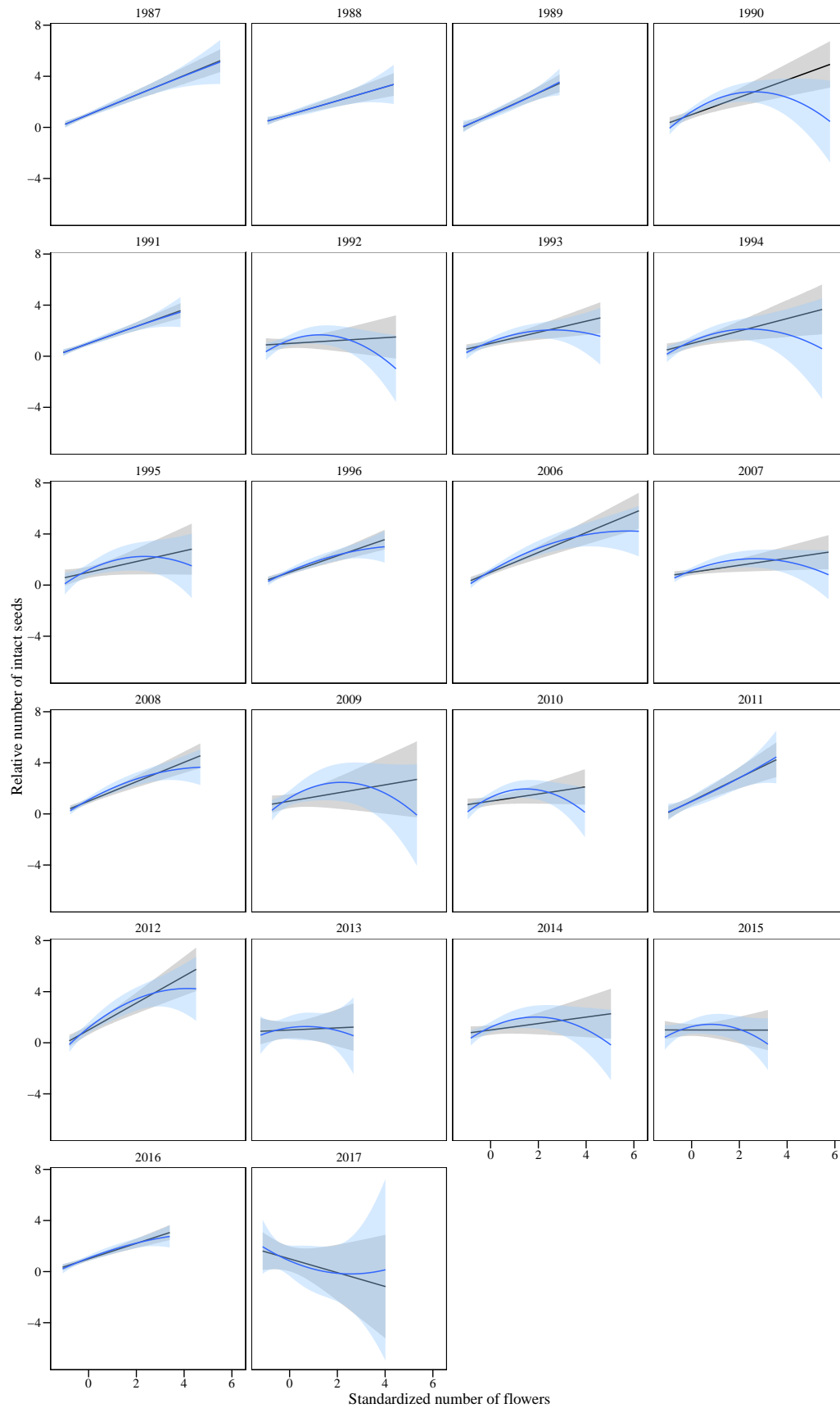


B)









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 = .)) %>% tidy(model))
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

```

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

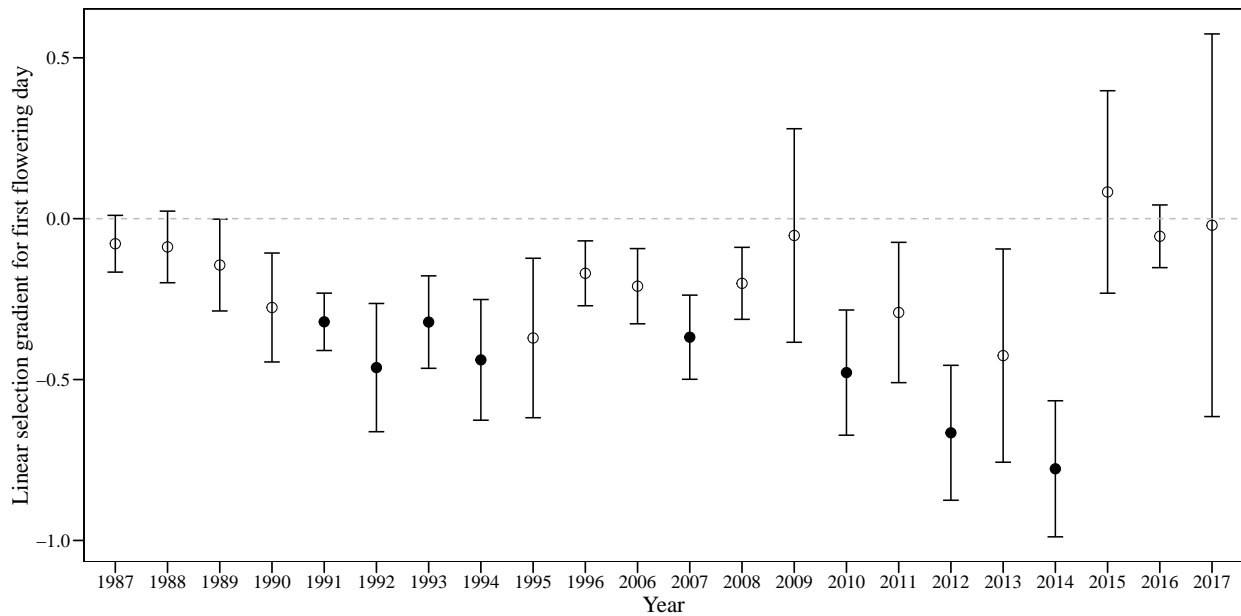
```

	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 confidence 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.

```

```
## 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.

## # 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.

## # 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.

## # 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.

## # 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.squared

## [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(mean,mean)))

## [1] -3.8  5.4

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

## [1] 1.5
```

Mean daily temperature April

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

## [1] 3.6 8.4

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

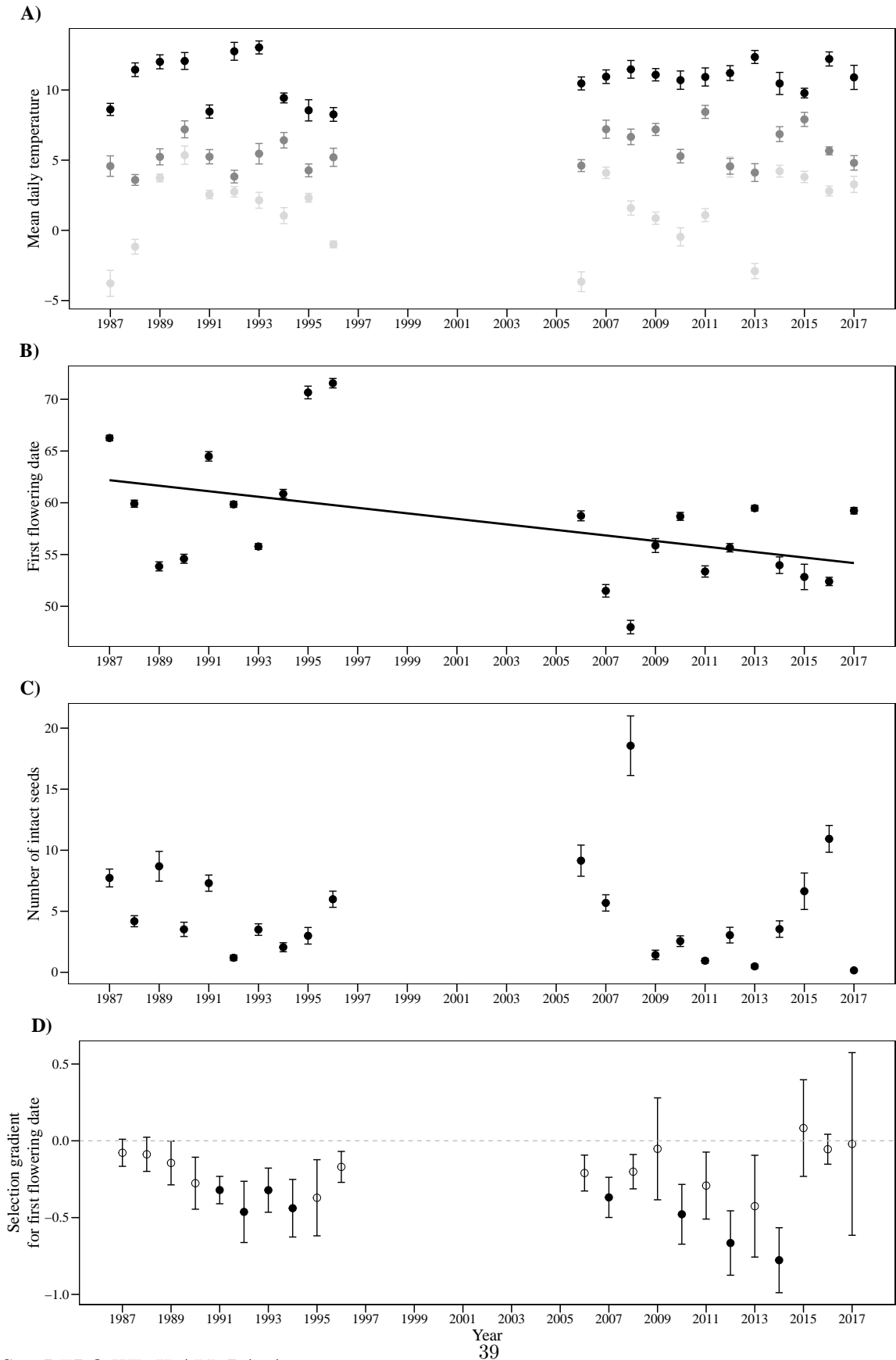


Fig.

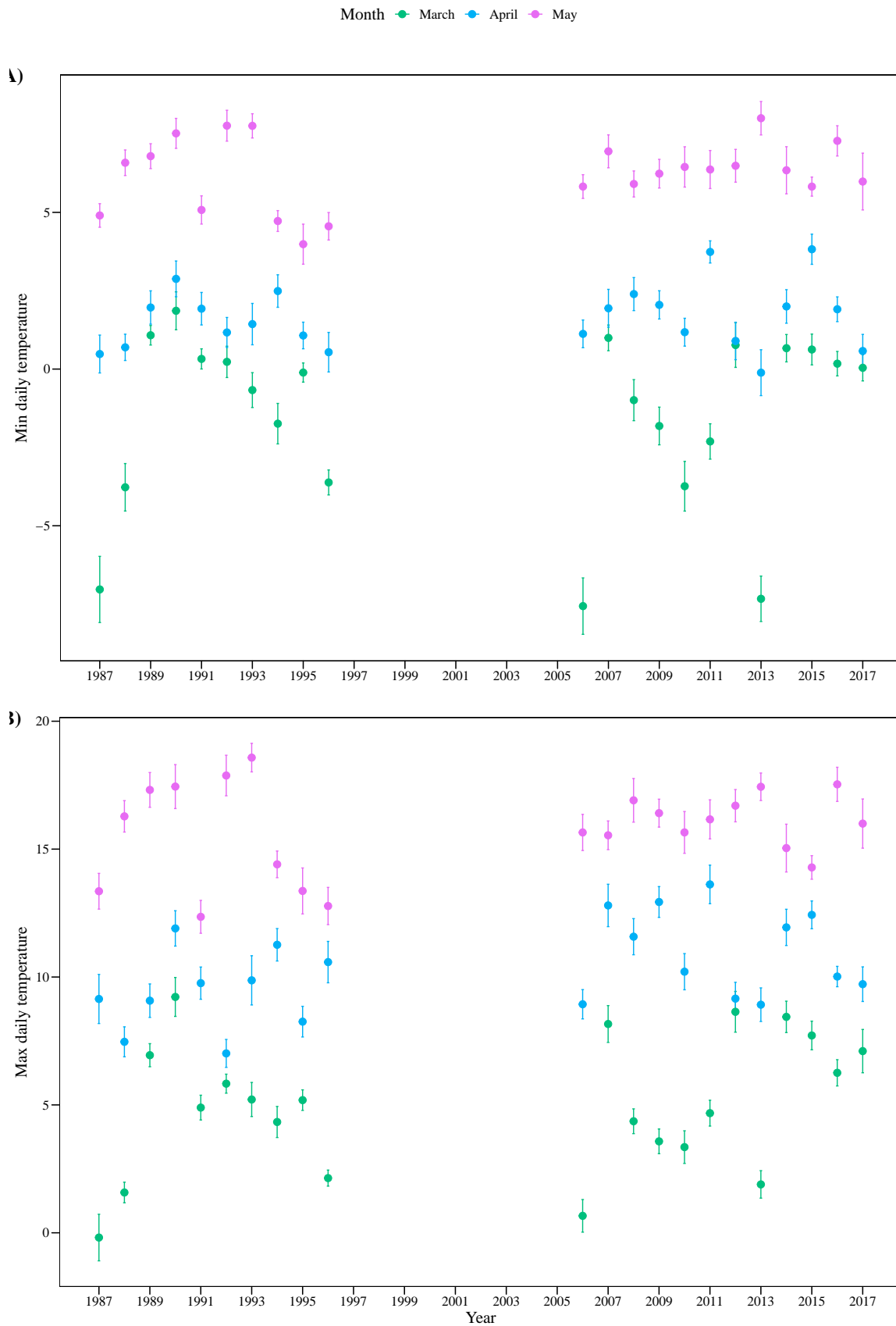


Fig. S2 - REDO WITH ALL DATA

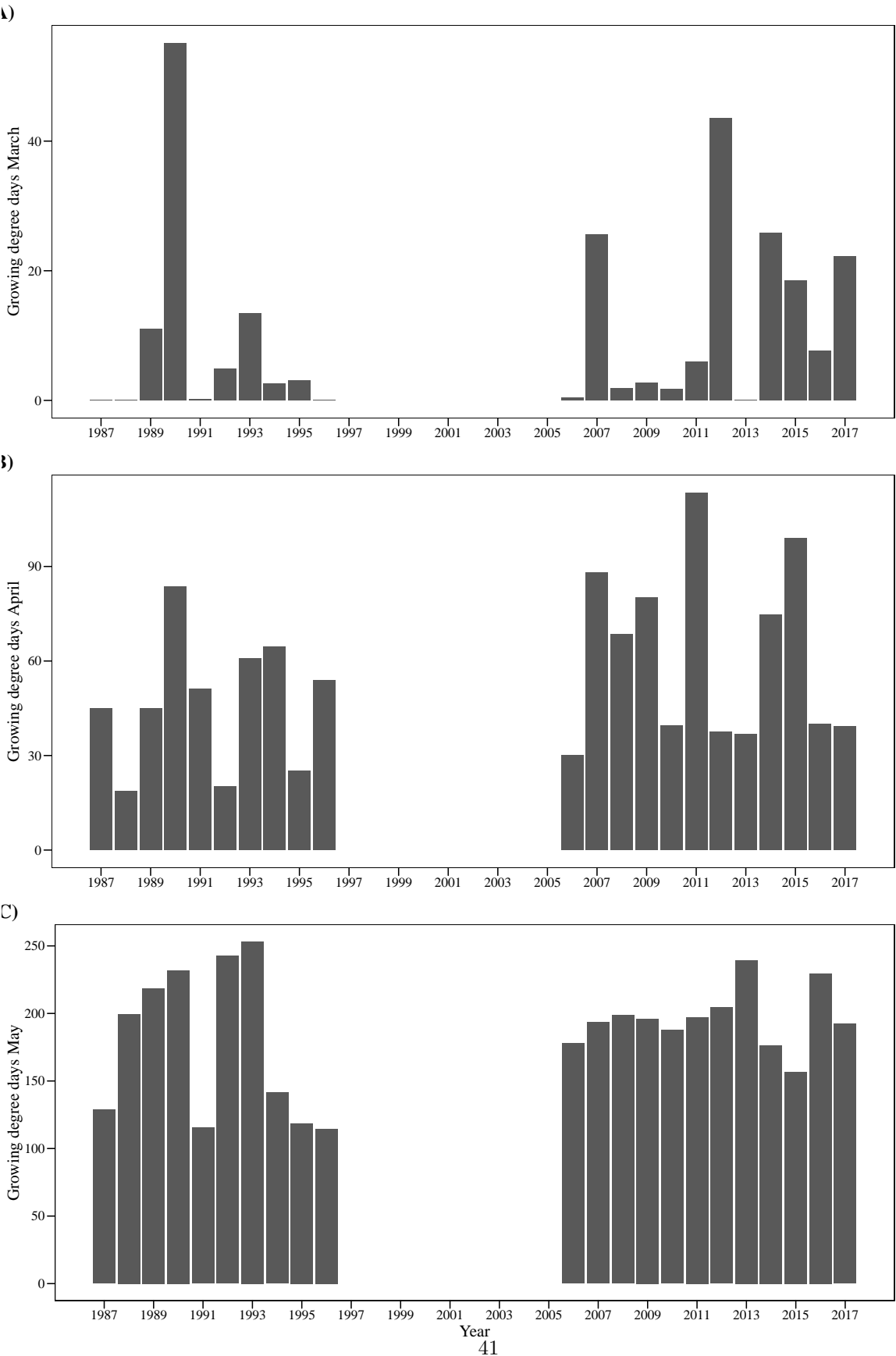
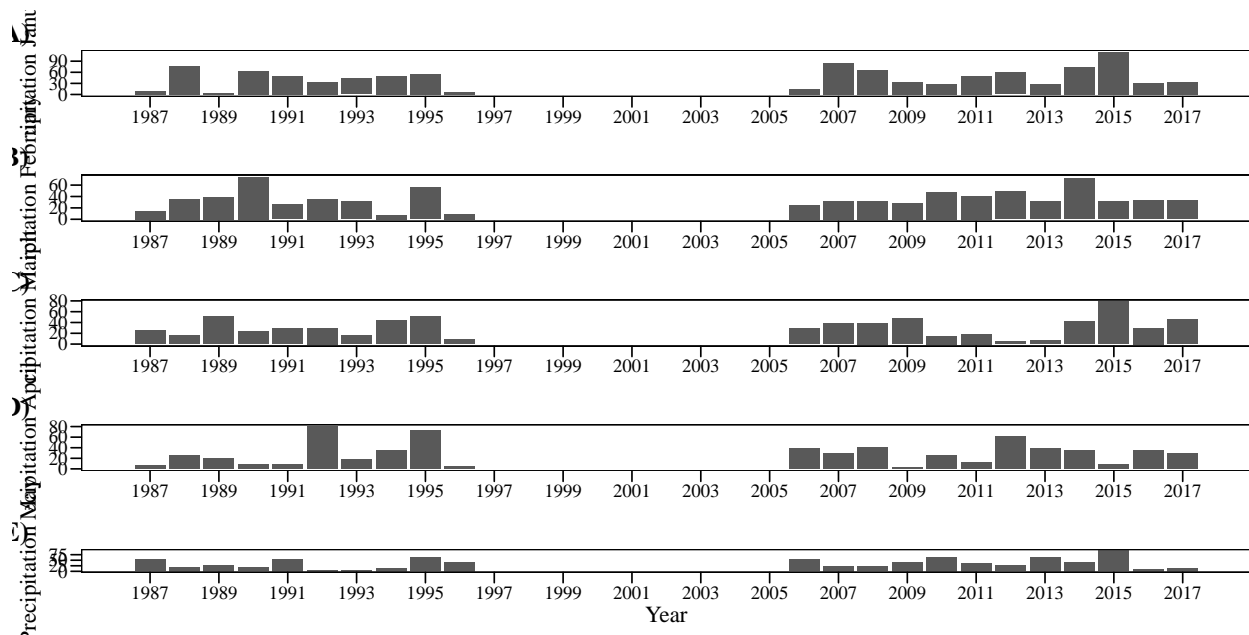


Fig. S3 - REDO WITH ALL DATA



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"

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
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.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)

```
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:
```

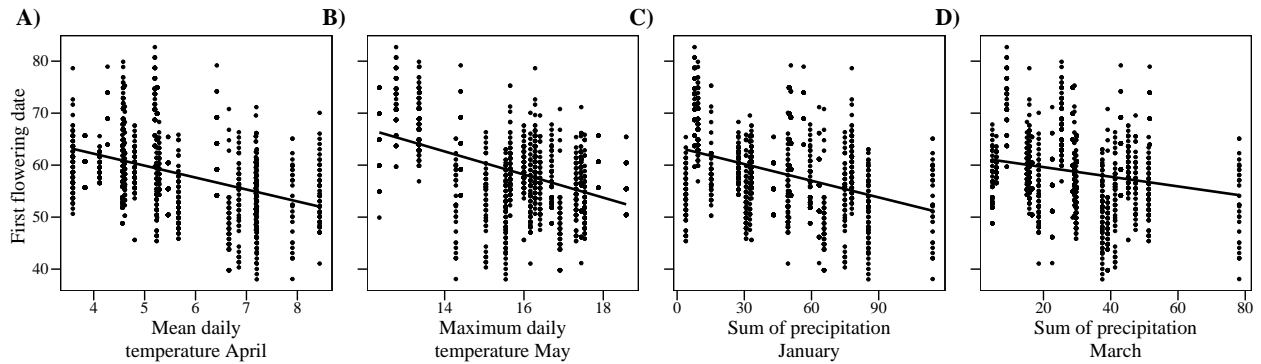
```

##      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.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)"

```

```

#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

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

## 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

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

## [1] 0.7602507

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)"

```



```
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

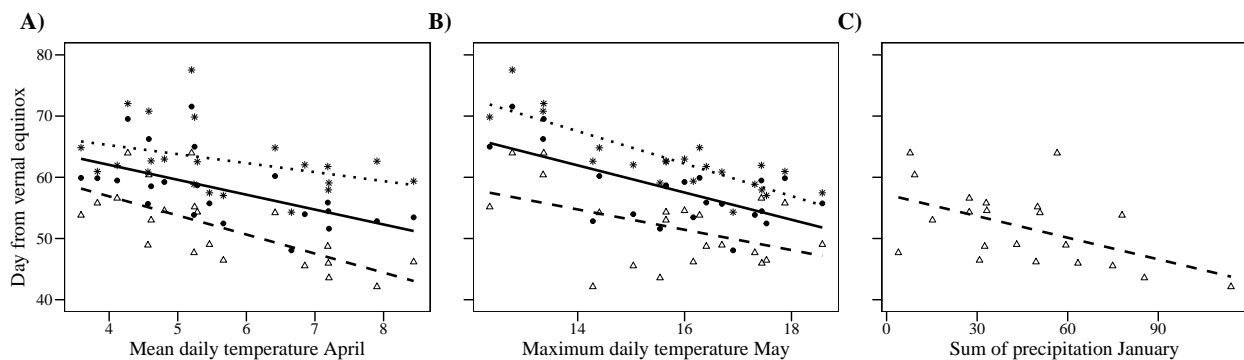
## date_90 also related to temp when including year (Table S4)
tidy(lm(date_90~scale(mean_4)+scale(max_5)+year,data=mean_weather4))

## # 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),
```

```

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

## Fixed term is "(Intercept)"
#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
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

## 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))

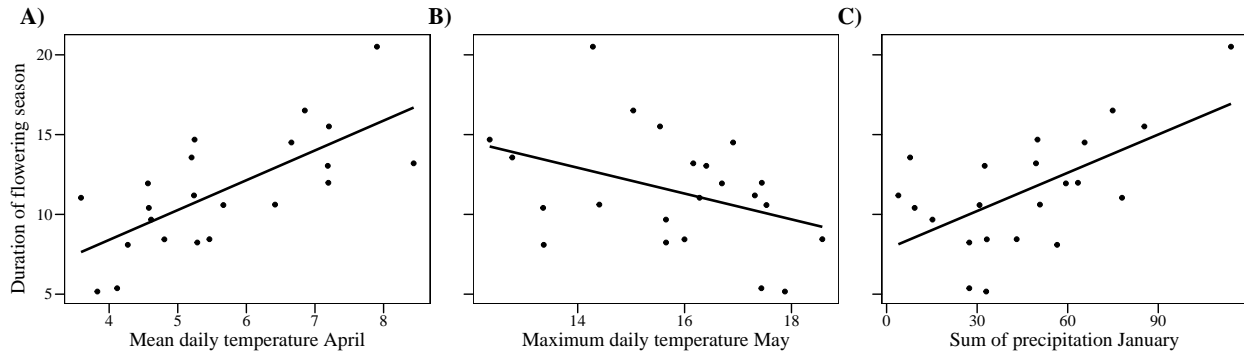
## # A tibble: 5 x 5
##   term                estimate std.error statistic p.value
##   <chr>              <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -0.940      93.1      -0.0101 0.992
## 2 scale(mean_4)       1.96       0.537       3.66 0.00195
## 3 scale(max_5)      -1.32       0.466      -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

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)"
```

```
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
```

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

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

Position (Table 2B)

```
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:
```

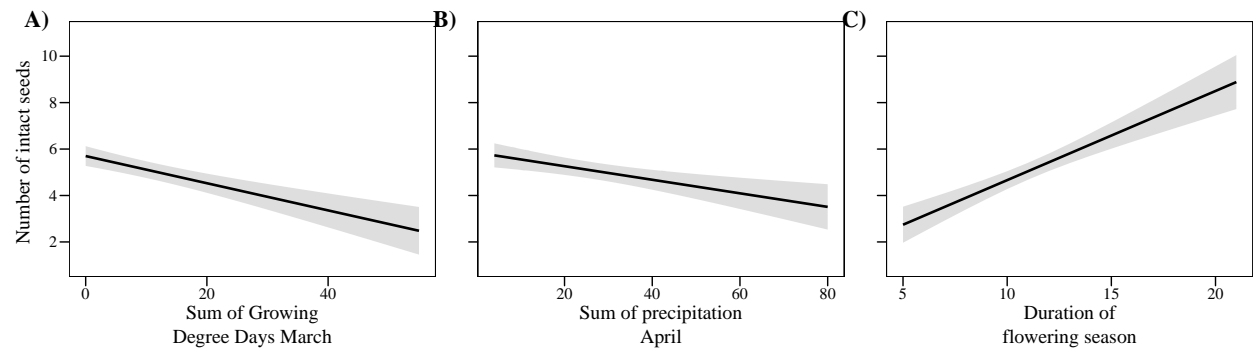
```
##          (Intr) d_90_1
## days_90_10 -0.940
## n_fl      -0.092 -0.105
```

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

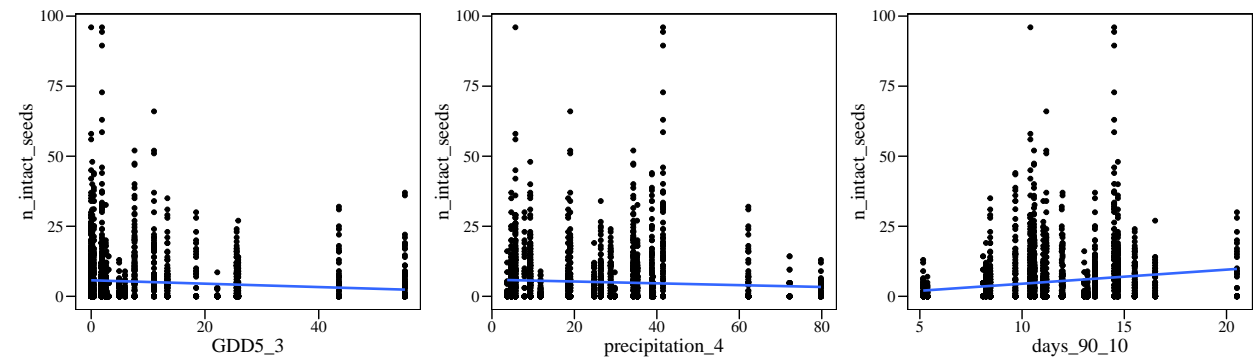
```
##          R2m          R2c
## [1,] 0.1743302 0.2189671
```

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)

```
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
```

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

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

GLMMs (Table 4)

```
# 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"

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

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

# 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:precipitation_4+(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

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

#No influences of FFD_mean on selection on FFD

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

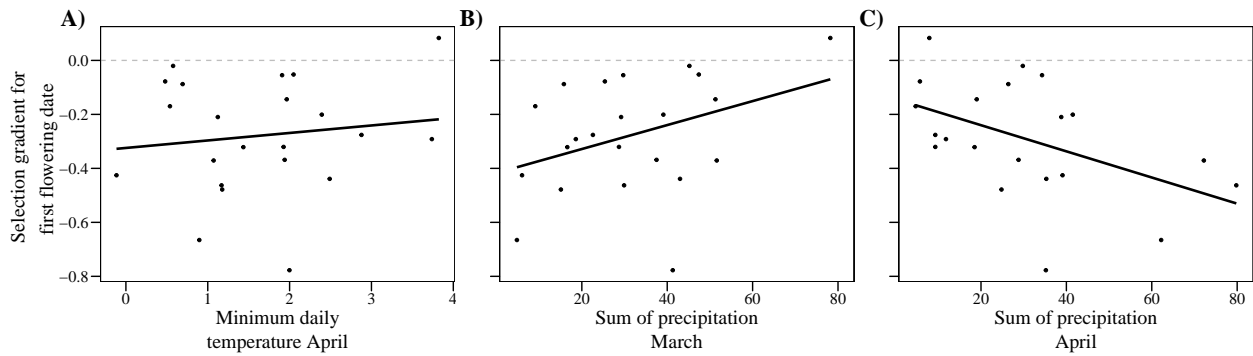


Fig. 6 alternative

